MODELLING AIRPORT CAPACITY CONSTRAINTS IN AIR TRAVELLERS' AIRPORT CHOICE

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1. INTRODUCTION

Over the next 20 years air transport demand (measured in revenue passenger kilometres, RPKs) is forecasted by the aircraft industry to increase by about 5% per year worldwide and between 4% and 5% per year in Europe (Airbus 2008; Boeing 2007). Thus RPKs may double within the next 15 to 18 years. Eurocontrol (2008) expects the number of flights to increase at an annual rate of 2.2% to 3.5% in Europe until 2030, depending on the future development of various political, environmental and economical factors. Here, the growth factor for 2030 in relation to 2007 lies within a range of 1.7 to 2.2. Capacity constraints already exist today at many airports and are becoming increasingly more important for the future development of air transport demand and supply. Efforts to ease constraints, in particular runway expansions to accommodate higher levels of demand for aircraft movements, take some time until they are actually implemented.

Capacity constraints include not only limited physical infrastructure like runways and terminals but also administrative restrictions like night curfews, noise & emission budgets or noise & emission limits, which all restrict the overall level of air travel demand an airport is potentially able to serve. If available airport capacity lies below the present or future demand potential of a particular airport, the airport choice of individual air travellers will be affected and will thus differ from a no-capacity-constraints case. Here demand potential of an airport is defined as the number of air travellers who choose a particular airport without capacity restraint. However, airport choice varies considerably when travellers are faced with capacity constraints, and thus depends on the gap between demand potential of an airport and the demand at capacity level. Thus it would seem appropriate to incorporate the impact of capacity constraints in a systematic and coherent way when planning studies on future airport choice.

Air travellers' first choice of a departure airport may not necessarily be a realistic one in a capacity-limited airport environment where demand exceeds supply at some airports. Therefore some air travellers will opt for second choice flight offers from other airports. The existence of sufficient supply at every airport, however, is a basic assumption of many passengers' airport choice models.

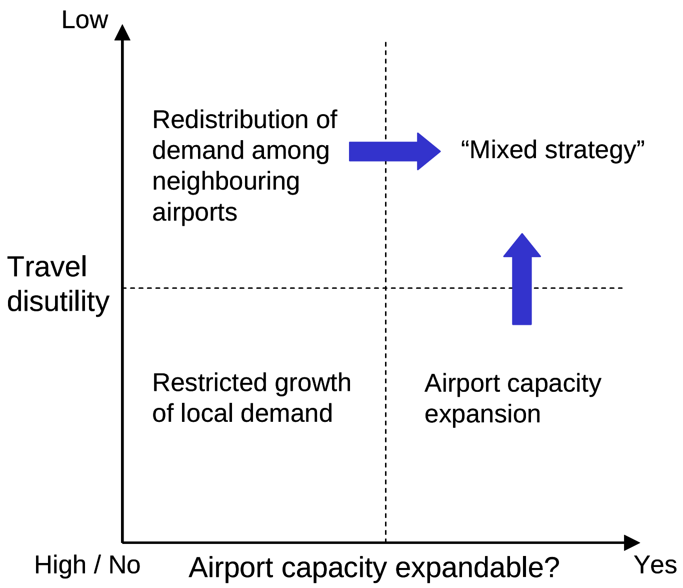

Figure 1: Impact of capacity constraints on airport choice (Gelhausen 2009)

Figure 1 demonstrates the possible consequences of capacity constraints at airports on the basis of two important factors as experienced by air travellers (Gelhausen 2009):

- Travel disutility relates to the efforts that air travellers have to take if they change their departure airport, leading for instance to increased travel time. These efforts are significantly less in a more decentralised airport environment with good road and rail access to airports than in a more centralised configuration with a lack of suitable alternative airports in a given choice situation.
- Whether airport capacity is expandable or not within a comparatively short time horizon depends on several factors, including geographical, political, ecological and economical variables. These factors differ from airport to airport.

Figure 1 also shows three basic future consequences of capacity constraints at airports (Gelhausen 2009):

- If travel disutility is high from the point of view of the air traveller and capacity expansion is possible, airport capacity expansion is a likely option at least over a medium time horizon.
- On the other hand, if travel disutility is low and capacity expansion is not possible, some air travellers might choose a neighbouring airport instead.
- However, if both travel disutility is high and capacity expansion is not possible, demand is partly lost and thus local demand growth restricted.

"Mixed strategy" describes an option between the first and second consequences; however, the precise definition depends on whether travel disutility or the possibility of airport capacity expansion is the major constraint.

Germany has a quite dense network of airports and therefore the focus of the empirical example of this paper lies on the second case, where the capacities of neighbouring airports absorb increasing air travel demand. Nevertheless, the new methodology described in the following chapters applies both to an airport system which has sufficient aggregate capacity as well as to an airport environment suffering from an aggregate capacity shortage.

The outline of this paper is as follows:

- Chapter 2 describes the methodological fundamentals of discrete choice theory and introduces the synthetic price concept together with its mathematical implementation.
- Chapter 3 is a demonstration of the capacity constrained airport choice model by means of an empirical example, which represents an excerpt from a larger case study by Gelhausen (2009).
- The paper closes with a short summary of the results and some conclusions.

2. MODELLING CAPACITY CONSTRAINTS IN AIRPORT CHOICE

2.1 Methodological background

The methodological basis of airport choice analysis in this paper is given by the concept of discrete choice theory. The basic hypothesis of discrete choice models is the assumption of individual utility maximisation. Utility represents an abstract real-valued measure of the subjective attractiveness of an alternative, computed by a function of the alternative attributes of each alternative, such as – in the case of airport choice – access cost, access time and supply of non-stop and low-cost flights to the chosen destination. In many cases a weighted sum of decision relevant alternative attributes forms this function, in which the weights depend on subjective preferences of the decision maker, in this case the air traveller. The decision maker is supposed to evaluate each alternative of his choice set by means of their utility value and chooses the one which maximises utility. However, in case of forecasting, utility of an alternative appears to be a random variable, mainly because of incomplete observability and measurability of the relevant alternative attributes from an external perspective. Therefore, the utility U_i of alternative i is described by a function, which includes both a deterministic component V_i and a random component ε_i, which obeys a stochastic distribution with expectation zero and a given variance (Maier and Weiss 1990, pp. 98ff.):

(1) $$U_i = V_i + \varepsilon_i$$

As a result, only evidence in terms of the probability of an alternative being the one with the highest utility can be given. However, summed up over homogenous market segments, these choice probabilities represent alternative specific market shares.

Different discrete choice model concepts have been developed which vary mainly in terms of their assumptions regarding the random component. The most prominent of these is the logit-model, which assumes independently and identically Gumbel-distributed random components for all alternatives (McFadden 1974, pp. 106ff.). Therefore, the choice probability of an alternative i is given by (Train 2003, p. 40):

(2)
$$P_i = \frac{e^{\mu V_i}}{\sum_j e^{\mu V_j}}$$

The scale parameter μ and the variance of the Gumbel distribution are inversely related, i.e. a high variance corresponds to a small scale parameter (Ben-Akiva and Lerman 1985, p. 104f). Figure 2 displays the choice probability P_i of alternative i subject to the utility difference between alternative i and the next best alternative j, which is denoted as (V_i – max(V_j)), and the variance σ of the utility function. The choice probability of alternative i rises with increasing utility difference to the next best alternative and vice versa. The steepness of the choice probability curve depends on the variance σ of the stochastic component of the utility function. Choice probabilities approach an equal distribution with increasing variance of the stochastic component of the utility functions; on the other hand they tend to be more distinct with decreasing variance. The choice probability P_i in Figure 2 is represented by a straight line parallel to the abscissa in the limiting case of an infinite variance, whereas a step function describes P_i in the case of no variance at all.

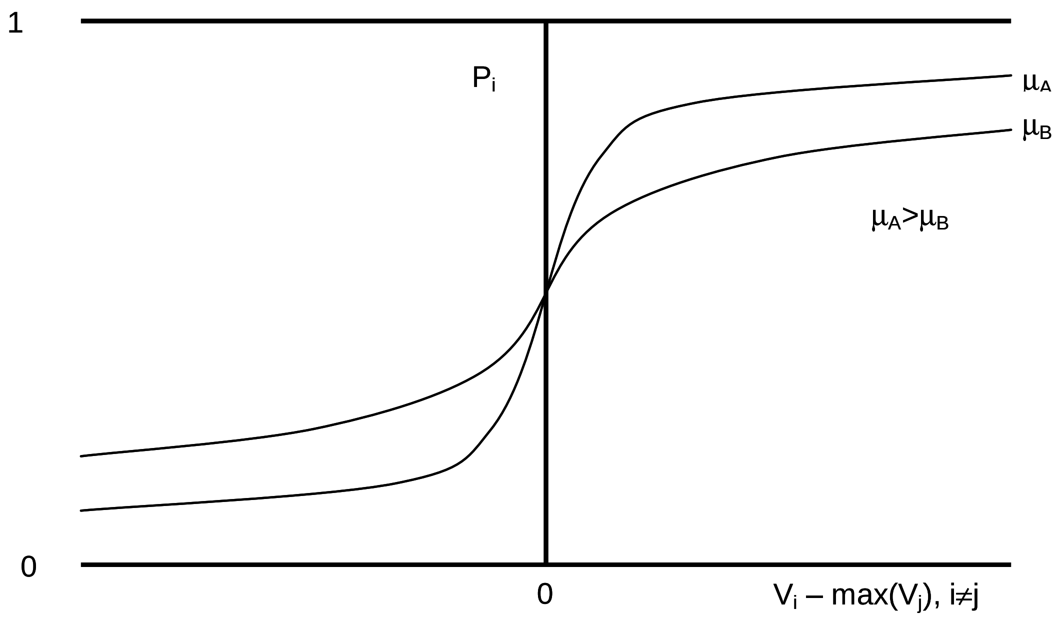

Figure 2: Choice probabilities in the logit-model (Maier and Weiss 1990, p. 140)

Figure 3 illustrates the main ideas of discrete choice models in a descriptive way (Gelhausen et al. 2008, p. 357). For a more detailed introduction and further concepts of discrete choice models see e.g. Ben-Akiva and Lerman (1985).

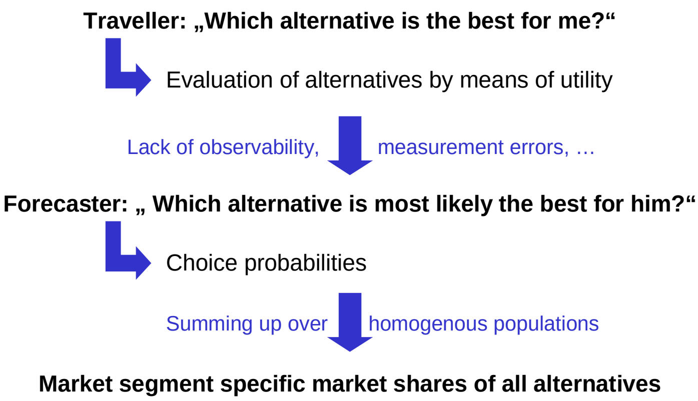

Figure 3: Concept of discrete choice models (Gelhausen et al. 2008, p. 357)

2.2 Including capacity constraints in discrete choice models

The principle of individual utility maximisation is employed to allow for capacity constraints within an airport choice model based on discrete choice theory. The loss of an air traveller's personal convenience due to limited airport capacity depends on the relative attractiveness of the alternatives in his choice set, i.e. the ensemble of possible departure airports. The more differently the traveller perceives them with regard to their attractiveness – representing a high value of (V_i – max(V_j)) in Figure 2 – the greater the loss of personal convenience is in case of a departure from an airport different from his original choice. However, the loss of personal convenience also depends on efforts necessary to depart from a particular airport suffering from congestion. These efforts may include early booking and paying a higher ticket price due to a higher degree of airport saturation. Hence, from an air traveller's perspective, there will be certain situations in which the necessary efforts to depart from a particular airport equal the loss of personal convenience due to departing from a less attractive airport. Thus it may not be possible to increase the overall level of personal convenience by either increasing additional efforts in order to depart from a more favoured airport or by decreasing efforts and departing from an even less favoured airport.

This individual utility maximisation process of air travellers is modelled by means of a so-called synthetic price, which represents an airport-specific statistic describing the demand/capacity situation. If an airport is unconstrained, the synthetic price takes a value of zero; otherwise it takes a value which is strictly positive. The synthetic price is intended to reduce airport attractiveness in the case of binding capacity constraints by making the airport more "expensive" from the perspective of the air traveller and thus reducing utility from choosing a congested airport. If the synthetic price increases infinitesimally, air travellers on the "preference fringe", i.e. those who are almost indifferent between various airports, switch to their next best alternative. Hence a greater gap between air travel demand and available capacity at an airport results in a higher value of the airport-specific synthetic price needed to meet capacity constraints. Equilibrium between demand and supply results when synthetic price levels are just raised sufficiently high. Figure 4 outlines the general procedure of the methodology.

Idea: The higher the loss in personal welfare (utility) from alternative to alternative, the higher the efforts to get a "slot" for the best alternative, e.g. by early booking or paying higher prices.

Realisation: Increase so-called "synthetic price" to reduce airport attractiveness and thus redistribute excess demand until capacity constraints are met.

Figure 4: Modelling capacity constraints in airport choice

The synthetic price concept represents a kind of rationing mechanism; however, this concept is not necessarily limited to capacity-induced (flight ticket) price adjustments. As already indicated earlier, a rationing mechanism based on "first come – first serve" may be implemented as well by means of the synthetic price concept.

However, the synthetic price concept resembles a sort of price level adjustment due to limited supply capacity assuming rational behaviour and the aim of profit maximisation on the supply side, i.e. airports and airlines. Hence, it would not be sensible to set prices below a profit maximising level. Therefore, by setting prices just high enough so that demand equals supply, profits are maximised, since air travellers with a lower willingness-to-pay are crowded out by passengers with a higher willingness-to-pay until supply equals demand. Thus, the synthetic price concept is similar to a price level index, which takes a value of zero at an unconstrained airport and rises with increasing congestion.

The results of the synthetic price concept represent a stable outcome between the demand and supply sides since from a game-theoretic perspective each player's action (demand vs. supply side) is a best response given the action of the other. Thus the outcome described qualifies as a Nash equilibrium (Nash 1950): Utility of the demand side and profits of the supply side are maximised.

If aggregate capacity of the total airport system is not sufficient to serve entire air travel demand, a so-called virtual airport with unlimited capacity is added. This virtual airport represents the least attractive alternative in the choice set of all air travellers and thus has a market share of 0% in an airport environment with sufficient aggregate capacity. However, if aggregate airport capacity is not sufficient to meet the entire demand, air travellers with the least loss of personal convenience, i.e. those with the lowest willingness-to-pay, are assigned to the virtual airport until capacity constraints are met. These air travellers represent unsatisfied demand potential and either switch to different modes of transportation or cancel their journey altogether.

2.3 Model theory

The synthetic price is added as a further variable with a negative coefficient to the deterministic component of the utility function, since utility decreases if the synthetic price is raised due to congestion. In principle, the coefficient of the synthetic price may take any fixed value less than zero (if the synthetic price increases, utility is reduced); the value of the coefficient only determines the level of the synthetic price in equilibrium between demand and supply without affecting the distribution of air travellers on airports. For now the coefficient is fixed to a value of minus one. Equation (3) shows the modified deterministic component V_i^{sp} of a linear utility function including the synthetic price; however, the reasoning which follows is not just limited to linear utility functions, which are chosen solely for ease of illustration. The utility function in turn is multiplied by the scale parameter μ of the Gumbel distribution such as in equation (2):

$$\mu * V_i^{sp} = \mu * \left(\sum_k b_k * x_{k,i} - x_i^{sp} \right) \tag{3}$$

b_k: Coefficient of attribute k including alternative-specific coefficients
$x_{k,\,i}$: Value of attribute k for alternative i
x_i^{sp}: Value of the synthetic price for alternative i
μ: Scale parameter of the Gumbel distribution

The value of the scale parameter has to be fixed to an arbitrary value to enable parameter identification in model estimation (Ben-Akiva and Lerman 1985, S. 107). Usually this arbitrary value is set to be one, as in this paper. Because of the proportional relationship between scale parameter and coefficients of a linear utility function there will be no substantial effect of the scale parameter on the synthetic price coefficient, when there is only a single model with a single utility function and a single scale parameter. However, to interpret the coefficient values of (3) in a meaningful way they have to be related to the scale parameter value μ (Maier and Weiss 1990, pp. 150f.).

If the model contains various sub models, e.g. in the case of different market segments, utility functions and their respective scale parameters may differ across sub models. Different market segments are subsequently indexed by MSi, where i characterises a particular instance of a market segment. Thus, the "effective" coefficients of a sub model are $\mu_{MSi} * b_{k,MSi}$ and the synthetic price coefficients of the different sub models need normalisation in order to be comparable across sub models since the synthetic price variable is defined per airport and its purpose is to raise the price of a congested airport identically for all market segments.

If the scale parameters of the sub models are set uniformly to a value of one, a possible method of accounting for differences in "true" scale parameters, based on the actual variance of the Gumbel distribution, is to multiply the synthetic price coefficient with the "true" scale parameter. However, this is not possible due to identification problems. Nevertheless, there is a proportional relationship between the synthetic price variable and its coefficient: If the coefficient is multiplied by a particular value and the variable divided by the same value there is no effect on choice probabilities. Therefore, only the ratios between the synthetic price coefficients of different sub models are fixed and thus their basic level has no effect on choice probabilities as it only changes the level of the synthetic price variables.

If vector x is multiplied by a constant scalar α, the vector length changes by a factor of α:

$$\alpha x \Rightarrow \alpha |x| \tag{4}$$

Thus, there is a proportional relationship between the scalar and the vector length. Applying this to the identification problem of the synthetic price coefficient ratios shows a possible solution: First normalise the coefficient vector of $V_{i,MSi}$ (excluding synthetic price) to unit length and set the scale parameters μ_{MSi} to a value of the length of the respective coefficient vector of $V_{i,MSi}$ before normalisation. The next step is to restore the values of the scale parameters and coefficient vectors of $V_{i,MSi}$ to their previous values before normalisation. The values of the synthetic price coefficients in $V^{sp}_{i,MSi}$ then equal the negative length of their respective coefficient vector of $V_{i,MSi}$ of step one before normalisation:

$$b^{sp}_{MSi} = -\sqrt{\sum_k \left(b_{k,MSi}\right)^2} \tag{5}$$

$b_{k,MSi}$: Coefficient of attribute k (including alternative-specific coefficients) of market segment MSi

b^{sp}_{MSi}: Synthetic price coefficient for market segment MSi

The coefficients of $V^{sp}_{i,MSi}$ comprise the coefficients of $V_{i,MSi}$ before normalisation and the synthetic price coefficients of (5). The synthetic price coefficients of (5) are proportional to "true" scale parameter values and variance of the Gumbel distribution respectively. Figure 5 is an illustration of this two-step process for determining the synthetic price coefficients.

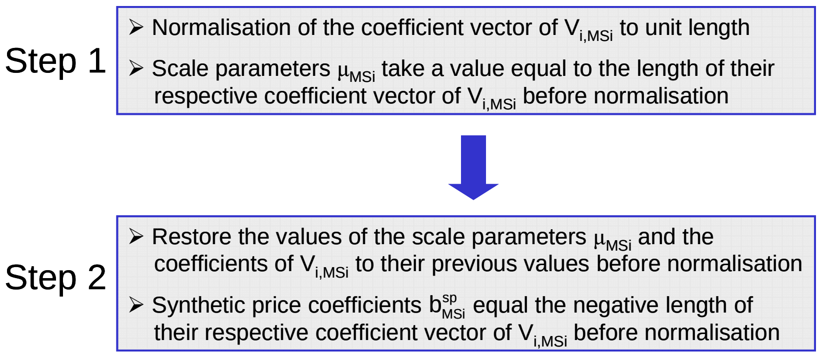

Figure 5: Modelling capacity constraints in airport choice

Figure 6 illustrates the relationship between choice probability, the value of the scale parameter and the synthetic price variable. A larger scale parameter μ_{MSi} results in a larger impact of the synthetic price variable on the choice probability P_i if $(V_i - \max(V_j))$ is close enough to zero. In the limiting case of the scale parameter μ_{MSi} going towards zero, the effect of a given value of the synthetic price variable diminishes. However, the effect of a given value of the synthetic price depends also on the relative attractiveness of alternative i for any non-zero scale parameter. The choice probability curve runs flatter the closer P_i is to either zero or one. Therefore, a larger absolute value of $(V_i - \max(V_j))$ leads to a smaller effect of a given value of the synthetic price variable on the choice probability P_i.

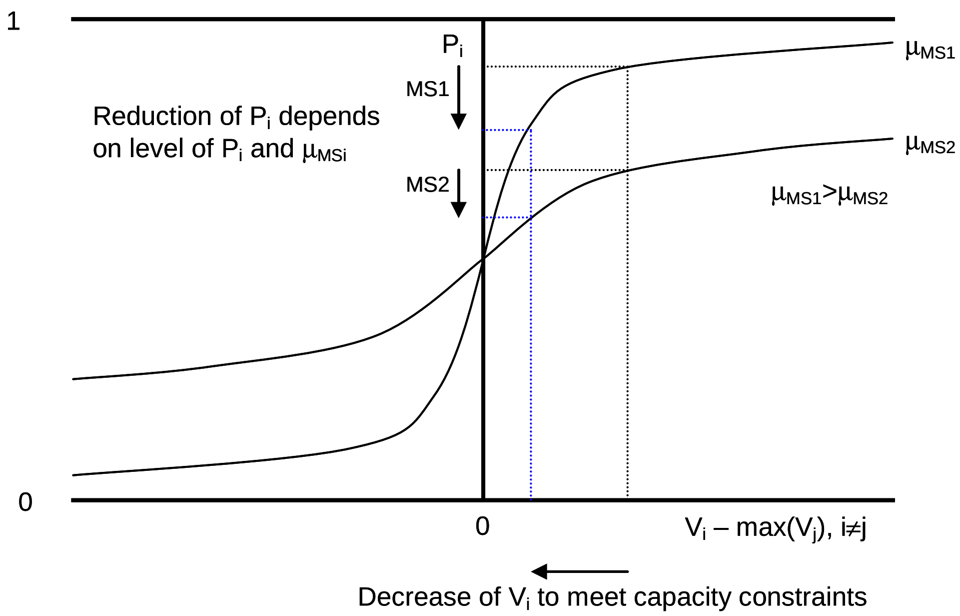

Figure 6: Dependence between scale parameter, synthetic price and choice probabilities

Therefore the full model is given by:

(6) $$\sum_{i,MSi}\left(\sum_k b_{k,MSi} * x_{k,i} + b^{sp}_{MSi} * x^{sp}_i\right) \xrightarrow[x^{sp}_i]{} \max$$

Subject to:

(7) $$\sum_{OD,MSi} y_{OD,MSi} * P_{i,OD,MSi} \le Cap_i \quad \forall i$$

(8) $$x^{sp}_i \ge 0 \quad \forall i$$

$y_{OD,\ MSi}$: Number of O-D air travellers from market segment MSi
$P_{i,\ OD,\ MSi}$: Probability of an O-D air traveller from market segment MSi to depart from airport i
Cap_i: Maximum capacity of airport i to handle O-D air passengers (e.g. per year)

The objective function (3) causes O-D air travellers to be assigned to airports with a minimum overall loss of personal convenience due to limited airport capacities. Side condition (4) ensures that capacity restrictions at every airport i are met. Side condition (5) means that the synthetic price cannot take negative values.

2.4 Solution algorithm

The problem (6) – (8) represents a complex nonlinear optimisation problem which is difficult to solve especially due to the nonlinear constraints (7). Therefore, a special solution procedure is proposed which exploits problem structure and represents a modified version of Simulated Annealing when compared with conventional approaches (see e.g. Kirkpatrick et al. 1983 or Salamon et. al. 2002).

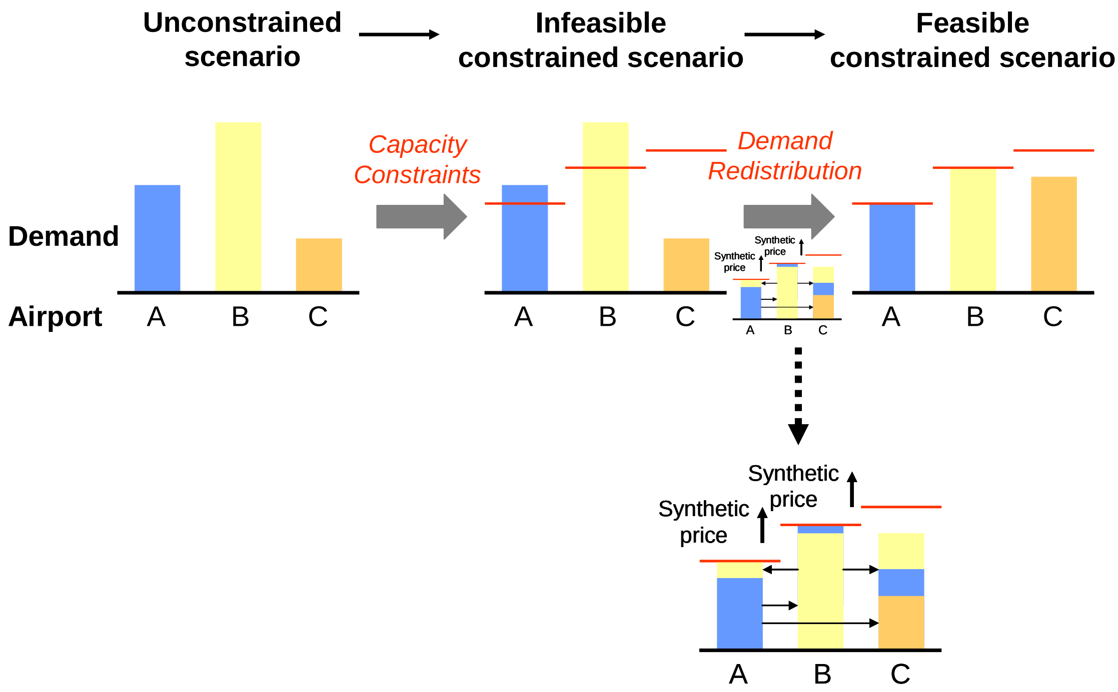

Figure 7: Schematic illustration of the solution procedure

There are two major differences: First, the algorithm starts with an infeasible solution and works towards an optimal or near-optimal solution which is respectively feasible or almost feasible. The initial point of the algorithm is a relaxed version of the problem where constraint (7) is omitted and synthetic prices take a value of zero for every airport, i.e. possible capacity constraints are removed. This is the so-called unconstrained scenario. In a second step capacity constraints are added, thereby leading to the so-called infeasible constrained scenario if at least one capacity constraint is violated.

Another difference compared to common approaches of Simulated Annealing is the interpretation of temperature: Here, the regulating devices are synthetic prices which may rise during the optimisation process to attain a feasible solution. Thereby capacity-exceeding demand is redistributed among airports.

The final solution represents the so-called feasible constrained scenario. Figure 7 illustrates the procedure subdivided into the three scenarios mentioned earlier.

A compact description of the solution algorithm follows:

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1. (Initialisation)

Start with the initial solution of the unconstrained scenario

2. (Main iteration)

(a) Add capacity constraints → infeasible constrained scenario

(b) Form set C which comprises all airports c where capacity constraints are violated

(c) WHILE CAP_c is violated more than $|\beta_c| \geq 0$ for any $c \in C$

(i) Choose arbitrary $c \in C$

(ii) Adjust x_c^{sp} so as to just meet CAP_c

(iii) Update C

END WHILE

3. (Final solution)

Final solution represents the feasible constrained scenario

The airport-specific constants β_c represent an arbitrary termination criterion and may be set to a small value to stop the algorithm if the solution is sufficiently close to the optimum and capacity constraints are thus not violated “too much”. From a practical perspective, a capacity difference of e.g. ten passengers per year has an almost negligible effect on final results; however, the algorithm finishes significantly faster. Therefore a near-optimal solution is justifiable as a final result.

3. AIRPORT CHOICE IN THE COLOGNE REGION: LIMITED AIRPORT CAPACITY

3.1 Study scope

The aim of this chapter is to offer a simple illustration of the model theory previously developed by means of an empirical example. This example represents an excerpt from some larger case studies of passengers’ airport choice in the Cologne region in Germany (Gelhausen 2008, 2009). The capacity constrained airport choice model is derived from an unconstrained airport and access mode choice model which serves as the base model. However, the focus of this paper lies mainly on the new methodology. A complete presentation of the empirical model details with regard to the underlying base model, such as estimated model parameters, would go beyond the scope of this paper. For this the reader is referred to Gelhausen (2007), Gelhausen (2009) and Gelhausen/Wilken (2006). The main data source for model estimation is the German Air Traveller Survey 2003 (Wilken et al. 2007). This survey is conducted at major German airports every few years and in 2003 more than 200,000 air travellers were interviewed at 19 international airports (e.g. Frankfurt/Main and Munich), as well as five regional airports (e.g. Frankfurt Hahn) to give a representative view of air travel behaviour in Germany. Figure 8 shows the national territory of Germany subdivided into 97 so-called spatial planning regions which are defined from a functional point of view and comprise regions of similar socio-economic conditions. The average population within a spatial planning region is about 850,000 and ranges from 238,000 up to 3.4 million. The German Air Traveller Survey 2003 shows that about 67% choose the nearest airport for departure; however, spatial planning regions are served by at least three and at most fourteen airports. On average, air travel demand of a spatial planning region is served by eight airports (Wilken et al. 2007, p. 172). Therefore, although two thirds of air travellers choose the nearest airport for departure, there is a considerable degree of competition between neighbouring airports.

The Cologne region is chosen as an example for analysing the effects of limited capacity to handle air travel demand on airport choice, since Cologne airport is located not far from other airports with both high demand and supply volumes. Figure 8 serves to illustrate the scope of the study: Air travel demand from the Cologne region is mostly served by Cologne airport (CGN), Düsseldorf airport (DUS) and the hub airport of Frankfurt/Main (FRA). Airport access from the trip origin to the departure airport is depicted by a solid line and the flight from the departure airport to the trip destination is illustrated by a dotted arc. The spatial planning region of Cologne is chosen as trip origin and the region of Berlin represents a trip destination for domestic travel, thus they are highlighted by a darker colour. All three airports have fast rail connections to the Cologne region. Frankfurt/Main airport can be accessed by frequent Intercity Express (ICE) train services giving a travel time from Cologne main station to Frankfurt/Main airport of approximately one hour. Therefore, this study represents the case of a rather decentralised airport environment, where travel disutility tends to be comparatively low (see the two north quadrants of Figure 1).

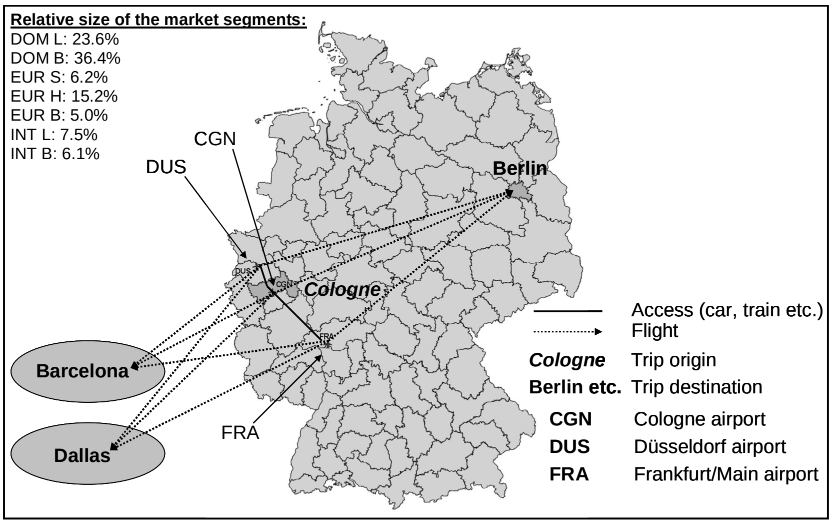

Figure 8: Scenario definition and Spatial Planning Regions of Germany (Gelhausen et al. 2008, p. 360)

Market segments have been identified by trip purpose and destination category with the purpose of reflecting behavioural differences. The model is thus developed and applied by market segment as follows:

- Journeys to domestic destinations, either for leisure (DOM L) or business purpose (DOM B)
- Journeys to European destinations for leisure purpose, subdivided into short-stay (up to four days, EUR S) and holiday (five days and longer, EUR H) trip
- Journeys to European destinations for business purpose (EUR B)
- Journeys to intercontinental destinations, either for leisure (INT L) or business purpose (INT B)

Three exemplary destinations have been selected to analyse airport choice by market segment:

- Berlin for domestic air travel
- Barcelona in Spain for European air travel
- Dallas in the USA for intercontinental air travel

All three aforementioned airports are connected by a non-stop flight service to Berlin and Barcelona but only Frankfurt/Main airport serves Dallas via a non-stop flight. Low-cost flights play a major role especially in European air travel. Both Cologne and Düsseldorf airport offer low-cost flights to Barcelona, however, the weekly flight frequency is significantly higher at Düsseldorf than at Cologne airport. Necessary data for analysis originates from different sources (Berster et al. 2005; Die Bahn 2005a, b, c; Deutsche Flughäfen 2005; INVERMO 2005; OAG 2005; Taxi 2005; Verkehrsverbünde 2005). Market segments were weighted by actual travel volume in summer 2005 at the aforementioned three destinations in the analysis to follow below. Their relative size is illustrated in Figure 8.

3.2 Impact of capacity constraints at airports on passengers' airport choice

Figure 9 displays the market shares of the total demand of the Cologne region served by neighbouring airports in relation to the unsatisfied demand potential of Düsseldorf airport. A value of 1 on the y-axis, which represents 100%, is the total demand of the Cologne region to Berlin, Barcelona and Dallas, i.e. the sum of all market segments. All other airports are assumed to have enough spare capacity to absorb any demand potential surplus from Düsseldorf airport. The market share of Düsseldorf airport decreases from 23% in the case of no capacity constraints, to 12% if the airport can only handle 50% of its demand potential. The excess demand of Düsseldorf airport is mostly served by Cologne airport: Its total market share rises from 71% to 82%, whereas Frankfurt/Main airport's share remains around 4% to 5%. Dortmund (DTM), Frankfurt Hahn (HHN) and Weeze (NRN) airports serve only a very small share of the demand of the Cologne region and their market shares increase only marginally due to constraints at Düsseldorf airport, since

Cologne airport is the more attractive alternative for air travellers originally wanting to depart from Düsseldorf airport.

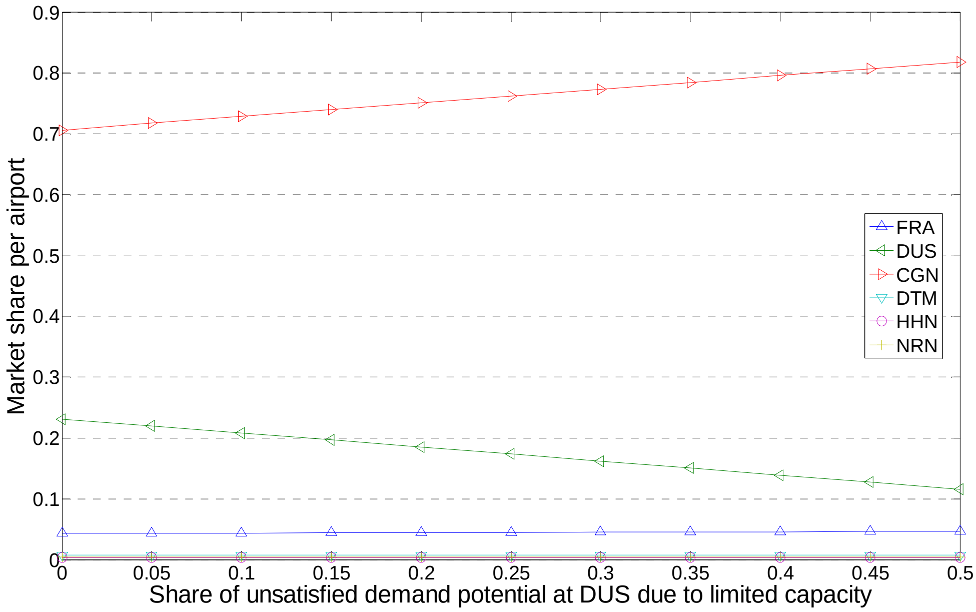

Figure 9: Total market share by airport in relation to unsatisfied demand potential at Düsseldorf airport (Gelhausen 2009)

Figure 10 shows Düsseldorf airport's market share by market segment in relation to the airport's unsatisfied demand potential resulting from capacity shortage. A value of 1 on the y-axis, which represents 100%, is the total demand of the Cologne region per market segment. The demand potential of a specific airport equals the number of air travellers who actually depart or would depart from this airport in an unconstrained airport environment. For example, a value of 0.05 on the x-axis represents an actual demand level of 95% of the whole demand potential. Thus a consequence of insufficient capacity at Düsseldorf airport to handle its full demand potential would be that 5% of air travellers who actually want to use Düsseldorf airport decide to depart from a different airport. The value of zero on the x-axis corresponds to a situation with sufficient capacity at Düsseldorf airport to serve its full demand potential. The question is then which air travellers precisely belong to this unsatisfied demand potential and which airport will they choose instead. If we assume that air travel demand will increase by 100% over the next 15 years, a value of 0.75 on the x-axis in Figure 9 and 10 represents a scenario in which Düsseldorf airport is only able to handle just 50% of the additional demand expected in the future (the demand potential of Düsseldorf airport doubles with the airport only being able to serve three quarters). All other airports are furthermore assumed to be capacity constraint-free.

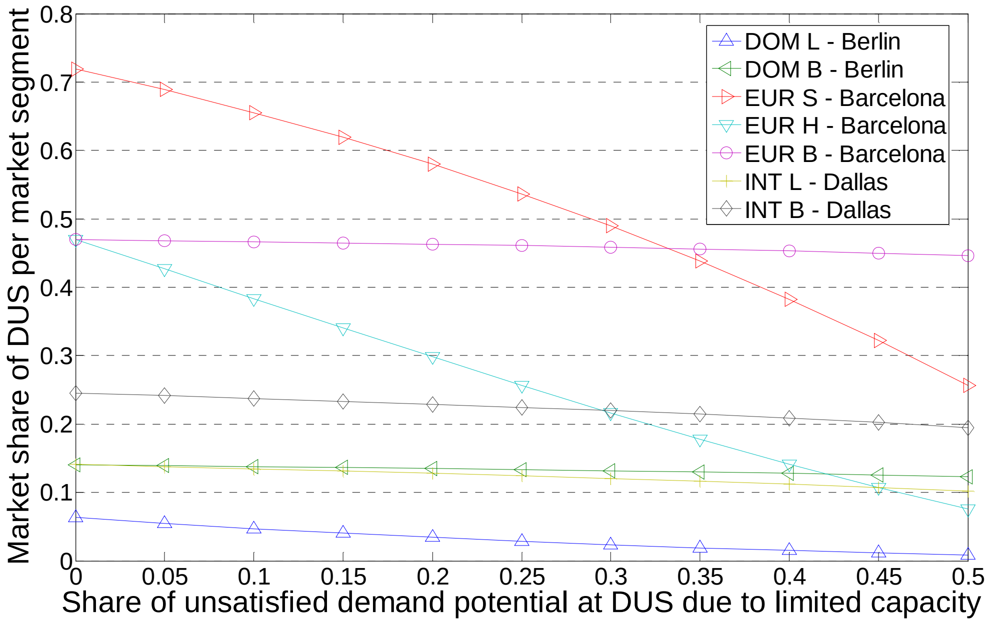

Figure 10: Market share of Düsseldorf airport by market segment in relation to unsatisfied demand potential (Gelhausen 2009)

Figure 10 shows that the crowding-out effects due to a capacity shortage at Düsseldorf airport are mainly at the expense of leisure air passengers travelling to Berlin and Barcelona. For example, if Düsseldorf airport can handle just 50% of its demand potential, its share of short-stay travellers to Barcelona falls sharply from 72% to 26% essentially because of their low willingness-to-pay and the fact that Cologne airport is an attractive alternative for departures to Barcelona. Similarly Düsseldorf airport's share of holiday travellers declines from 47% to about 8%. It should be noted, however, that the assumption that Düsseldorf airport will only be able to serve half of its (future) demand is a rather radical one and unrealistic at least for the near future. This assumption serves only to show the underlying model mechanism thus emphasising the effects of limited capacity on passengers' airport choice.

On the other hand, airport choice of travellers in business segments depends more on lower access times than on lower ticket fares and thus remains comparatively stable: The share of domestic business travel to Berlin only declines from 14% to 12%, the market share of European business travel to Barcelona goes down from 47% to 45% and intercontinental business travel from Düsseldorf airport to Dallas (via stop-over flight) is reduced from 25% to 19%.

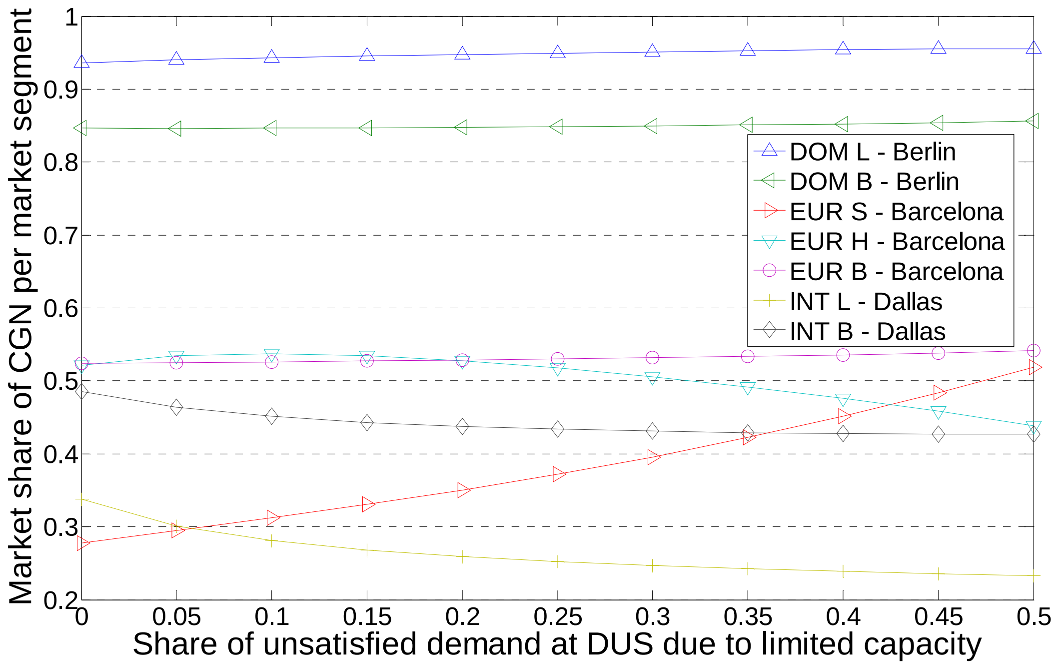

Figure 11: Changes in passenger distribution at Cologne airport in relation to unsatisfied demand potential at Düsseldorf airport (Gelhausen 2009)

If one assumes that Cologne airport is already operating at its capacity limit and thus not able to absorb any excess demand from Düsseldorf airport, its overall level of air transport demand served remains fixed. However, Figure 11 illustrates the distinct distributional changes among the seven market segments. This figure shows the market segment-specific shares served by Cologne airport, with a segment-specific demand of the Cologne region of 100%. As an example, about 95% of domestic passengers from the Cologne region, who travel for leisure reasons, use Cologne airport as departure airport in the no-constraints situation at Düsseldorf airport. With increasing capacity shortage at Düsseldorf airport, there is only a slight increase in Cologne airport's market share in the segments of domestic (Berlin) and European (Barcelona) business travel. However, Cologne airport's share of short-stay air passengers to Barcelona increases clearly from 28% to 52%. These passengers are crowded out at Düsseldorf airport because of their low willingness-to-pay and choose Cologne airport rather than Frankfurt/Main airport because of the large number of low-cost flights from Cologne. On the other hand, the market share of holiday travellers to Barcelona from Cologne airport first rises slightly to 53% due to increasing capacity shortage at Düsseldorf airport, but then falls to about 44%, since these users become increasingly displaced by the volume of short-stay travellers to Barcelona. Changes in market structure at Cologne airport mainly happen at the expense of the segments of intercontinental travel to Dallas: Here leisure travel declines from 34% to 23% and business travel from 49% to 43%. Passengers switch to Frankfurt/Main airport, basically because good road and rail access to and the number of non-stop flights from Frankfurt/Main mean losses in personal convenience remain small.

4. SUMMARY AND CONCLUSIONS

This paper describes an integrated method of accounting for limited capacity in a passengers' airport choice model based on discrete choice theory.

The model is based on the principle of individual utility maximisation. However, the discrete choice model is refined in several ways to achieve a high degree of integration: Nonlinear programming is employed to formulate a capacity constrained discrete choice model. A modification of Simulated Annealing which has been adapted to the model structure is employed as solution procedure to find an optimal or near-optimal solution. The model is embedded within a game-theory framework to guarantee a solution of the problem, which represents a stable equilibrium between airlines/airports and air passengers, i.e. each player chooses his best response given the action of the other player.

Since the model is backed up by rational choice behaviour, it is possible to analyse the impact of a capacity shortage in the airport system on a microscopic level of individual air travellers. Hence, detailed evidence on how a particular capacity shortage affects individual airport choice behaviour emerges. The exemplary case study of airport choice in the decentralised airport environment of the Cologne region in Germany shows up clearly that limited capacity for handling air travel demand at one airport alters choice behaviour considerably in comparison with an unconstrained scenario. There are basically three major consequences of limited capacity at airports (Gelhausen 2009):

- Capacity constraints lead to serious spill-over effects, thus changing market structure and resulting in secondary capacity constraints at additional airports depending on the degree of capacity shortage. These spill-over effects are usually complex in nature.
- Therefore, depending on the extent of capacity shortage, air travel demand is distributed among more airports and thus airports, which were previously less attractive from the perspective of the air traveller, may benefit from the situation.
- However, airport congestion diminishes personal convenience of air travellers, because of e.g. increased travel time, travel cost and a more unfavourable flight schedule.

The methodology proposed in this paper is general in nature and therefore applicable to other problems of travel behaviour analysis and discrete choice theory. A main advantage lies in the fact that it is possible to expand an already existing unconstrained discrete choice model with little effort into a model with capacity limits. Therefore it is not necessary to create a new model from scratch to account for limited capacity in an already existing model. Moreover, both the value of the synthetic price and its coefficient are calculated endogenously within the model for each airport. Hence there is no need to supply an exogenous price premium due to a capacity shortage for each airport and market segment, which may be difficult to determine precisely in reality.

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