METHODOLOGY OF PASSENGER DEMAND SIMULATION FOR THE EVALUATION OF FUTURE AIR TRANSPORT CONCEPTS

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Abstract

This paper describes a modelling approach of passenger´s individual booking behaviour based on utility maximisation theory. Flight alternatives with their different itineraries are modelled inside the simulation based on ticket, flight schedule and operating airline attributes. These attributes are than evaluated by each passenger based on derived cost functions depending on geographical, socio-demographic and behavioural passenger properties. The alternative with the lowest costs (highest utility) is chosen and the booking is assigned to the simulation. The simulation of this individual booking behaviour leads -on an aggregate level- to passenger demand and expected yields, which are one of the most important factors for airline´s. The simulation is validated on real booking data from air traffic inside the USA. With the flexible and open structure, demand and yields for future transport concepts with changed operational issues, like design cruise speed or design block range, can be determined.

1. MOTIVATION

Aviation is focussing tremendous challenges in terms of reducing environmental effects onto climate change. Hence, the Advisory Council of Aeronautics in Europe (ACARE) set up the Strategic Research Agenda (SRA-1) to determine targets for environment, air transport efficiency and quality and affordability for future air transport concepts. For environmental issues, ACARE targets a Co_2 reduction for the world fleet in 2020 of 50% and a NOx reduction of 80% compared to the world fleet of 2000 [1]. To fulfil these targets many researchers around the globe started with the design of new aircraft concepts with different technologies. Aircraft design studies with a change of design range, cruise speed together with a change of cruise altitude show great potential to meet partly the ACARE targets [2],[3],[4]. Especially the so called “Ultragreen” aircraft configuration in [4] with its flight mach number of 0.76 and a reduced design range of 4,000nm shows great potentials to meet the ACARE goals. With a change of flight speed and design range, these concepts have a significant impact onto airline´s operational issues.

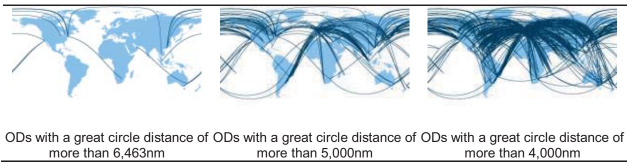

Figure 1 Visualisation of the effected worldwide origins and destinations for direct flights with reduced design range of 6463nm, 5000nm and 4,000nm (data from OAG 2004[5])

Figure 1 visualises the effect of changing design range of future long-haul aircraft onto airline´s operations. Besides the effect onto airline operations, these new concepts will also have a significant impact onto the passenger´s. It can be assumed that with these new concepts an increase in stops and additional travel time can be observed. On the other side, air transport has to economically feasible. This is valid for today´s and near term aircraft configurations (like B787 or A350) and should be valid for future air transport concepts as well. To evaluate economic feasibility of such new concepts, simplified assessment based direct operating costs can be used. There are dozens of methods of different stakeholder in aviation (e.g. Boeing, Airbus, AEA etc…) available to calculate these costs, whereas models determining expected passenger demand and yields are very rarely. Therefore, this paper describes a methodology how to simulate passenger demand and how airline yields can be determined for future air transport concepts with changed operational properties.

2. INTRODUCTION INTO PASSENGER ITINERARY CHOICE PROBLEM

Passenger demand and airline yield can be explained as aggregated results from passenger´s individual booking or choice behaviour out of flight alternatives with different attributes.

2.1. Historical and theoretical background

Discrete choice models were developed in the last century by psychologist to explain rational behaviour [6,7,8]. Researcher in the field of Economy used discrete choice models since 1980s in an extensive way [9],[10],[11] and [12]. Discrete choice models in the field of transport were applied since 1962 with trade-offs between travel time and travel costs to assess alternative transportation projects. A detailed description of the historical background can be found in [13] and [14]. Summarizing it can be said that discrete choice models for transportation application are fully accepted by scientists [14], [15] and [16].

2.1.1. Framework of discrete choice theory

The discrete choice theory states that -if individuals are faced with a choice problem -*individuals* are choosing an *alternative* out of a *choice set* with the *highest personal utility* coming from *alternative´s attributes*. This is also called utility maximisation principle and follows rational choice theory. Transferring this theory into passenger itinerary choice problem, following definitions should be made. An *individual* is here an individual passenger with his individual characteristics. When such a passenger is evaluating different flight options with different itineraries, these itineraries can be called *alternatives*. All alternatives which are considered in his choice, is *passenger´s individual choice set*. A flight alternative or itinerary can be described by different *attributes* like departure time, number of stops or operating airline. The utility from an alternative, precisely from its attributes can be calculated based on utility or costs. The alternative with the lowest total costs out of the choice set is then taken, or -in this context- a flight alternative is booked. It should be mentioned that a detailed description of the entire theory nad modelling techniques can be found in [13] and [14].

3. PASSENGER ITINERARY SIMULATION MODEL *PARIS*

In the following chapters, the structure of the passenger itinerary simulation model *PARIS* will be described in detail. The overall simulation can be divided into four steps. The first step deals with the definition of the decision maker, here the individual passenger. The second step determines with the help of a path finding algorithm the individual choice set including all possible flight options/itineraries. The third step deals with the evaluation of all possible flight itineraries. This evaluation is done based on cost functions for ticket, schedule and airline properties. The last step is the assignment of an individual passenger on a specific itinerary, which has the lowest generalized personal cost. The first step is conducted at the beginning of the simulation (passenger’s initialising). All other steps are done loop wise for all passenger´s in the simulated region.

3.1. The decision maker - Modelling passenger characteristics

To simulate passenger booking behaviour or precisely itinerary choice, a few passenger characteristics have been identified influencing the booking behaviour. These characteristics can be summarized in geographical, socio-demographic and behavioural criteria, which lead to a passenger segmentation by these criteria.

3.1.1. Geographical passenger segmentation

As a first step inside the simulation, the investigated regions/markets have to be determined. The world –inside the simulation- is divided into 17 different regions according to the definition of OAG.

Figure 2: Definition of regions worldwide acording to OAG[5].

For validation in the last chapter, only the USA as part of North America (NA1) was used. To simulate passenger itinerary choice on transatlantic routes (routes between NA1 and EU1), three markets have to be simulated, namely NA1, EU1 and the transatlantic market NA1-EU1 and EU1-NA1 respectively.

3.1.2. Socio-demographic passenger segmentation

Socio-demographic segmentation criteria includes beside demographic factors like age, gender, family status or household size also socio-economic criteria like occupation/travel purpose or income. Inside PARIS, passengers are modelled by their travel purpose, income, occupation, age and gender.

To determine the percentage of business and private traveller in a market, a simplified approach was chosen due to missing route-specific distribution database. According to [17], it was assumed that each city in a country has the same distribution of business and private traveller as the whole country, as stated in the database.

The age distribution as well as gender distribution was also taken from ONS database and set to be fixed for all cities inside one country. The monthly household income, which strongly influences passenger booking behaviour, was modelled depending on passenger´s age and gender [56]. It could be shown that passengers with higher income are willing to pay more for air fares than passengers will lower monthly income. This willingness to pay (WTP) is modelled based on studies from [18] and extended by results from [56]. Inside *PARIS*, WTP is depending directly on income and travel purpose.

3.1.3. Behavioural passenger segmentation

Behavioural passenger segmentation criteria are inside *PARIS*, length of stay, departure day, booking day, number of undertaken flights per year, the membership and status of frequent flyer programs and preferred cabin class.

Length of stay was determined by ONS database and depends on travel purpose and OD distance. Mean values for length of stay are increasing with increase of OD distance. Generally, business trips are shorter than private trips. The departure day during a week is determined by data from [28]. Out of this study, most of all trips are done during Monday to Friday, if length of stay is zero to one day. If length of stay is longer than six days, distributions become uniform. The booking day is needed for initialising the passenger´s. At the beginning of a simulation run, all passengers are sorted by their booking day. The booking day can be determined by their departure day minus advanced booking period in days. The advanced booking period has be obtained from booking request curves [19] and differentiated between business and private travellers. Private travellers tend to book air trips longer in advance than business travellers. This booking behaviour is taken into account inside PARIS. Number of undertaken flights per year was determined by age, income and travel purpose and is obtained from [20] and [21].

Frequent flyer programs (FFPs) were firstly introduced by American Airlines 1981 and most airlines offer frequent flyer program, either their own or as a partner of another airline. [22] stated that number of frequent flyer programs doubled since last 15 years. [23] stated three primary factors why these programs are so successful and widely introduced by airlines. The first reason is to develop and strengthen passenger´s loyalty towards one airline. This reason was the case when American Airlines introduced the first FFP. FFP also enables a product differentiation between airlines, which is the second reason. The third reason deals with data from participating passengers. These data are very useful to identify travel behaviour and habits of passengers to customize marketing programs.

[23] identified that 2/3 of all members of a FFP are influenced by this program when choosing a flight. Even if FFPs are mostly not the primary decision criterion for booking a flight alternative, but their strong impact is also described by [24,p.239] and [25]. Therefore, the probability of being a member of a FFP is taken from [26] depending on airline market share at the origin as well as passenger´s number of undertaken flights per year. For business travellers it is also necessary to determine their occupation as well as monthly income to derive a travel policy for these occupations. A travel policy inside a company leads to restrictions, which cabin classes (First, Business or Economy Class) can be booked by different business travellers. Travel policies were investigated by [27] and results were directly used inside *PARIS*.

3.2. The choice set - Modelling flight alternatives

After passenger characteristics have been setup and determined, this chapter describes a technique how to derive flight alternatives with their attributes as flight options for the virtual passenger. One the one side, set of attributes of the flight alternatives are directly linked to the flight schedule (e.g. departure time, arrival time, properties of stops etc.).This will be explained in chapter 3.2.1. On the other side, the algorithm should determine possible air fares for a specific routing. The determination of these fares depending on a routing will be explained in chapter 3.2.2.

3.2.1. Path finding algorithm

The aim of the path finding algorithm is the definition of “possible” as well as realistic flight options or flight alternatives from a database. The used database was obtained from [5]. Unfortunately, OAG consists only of single direct flights; hence the algorithm should combine these single flights in a framework of heuristics to realistic itineraries. The heuristics were derived from a second database, which consists of more than 600,000 routings between 10,000 most flown ODs worldwide. This database was setup by an automatic querying of an internet-based travel agency in 2008. The first heuristic defines airline-specific hub- and non-hub airports. Connections only at these hubs are allowed. The second heuristic is the maximal allowed number of stops between an origin and a destination. Real data showed that in the USA, only 2.4% of all passenger´s have booked an itinerary with more than two stops. Real data from -e.g. [28]- showed less percentages for Europe. The algorithm does not search for routing with more than 2 stops. The next heuristic is the minimum connecting time (MCT) at hub airports. The minimum connecting times is the time or duration passengers need to change the gates, aircraft and/or airlines. This time is guaranteed by airports and depending on airport´s infrastructure as well as the OD. The dependency of MCT by OD combination can be explained by different procedures as well as regulations for handling connecting passengers. Therefore, there is no constant MCT per airport. The implementation of OD-specific MCTs into the simulation would lead to a significant amount of required data. On the other side, a constant MCT for all airports would penalize airports with short MCT. Hence a compromise between required data and accuracy was implemented into the algorithm. Due to existing database of more than 600,000 routings including huge amount of itineraries with stops, a minimum value per airport could derived based on transit times of these routings. Comparing these airport-specific MCTs with data provided by airports around the world, a good correlation could be observed.

Codeshares enable airlines to offer and sell flight tickets under own flight numbers, which are operated by other airlines partly or totally [29], [30]. On the other side, airline alliances like Star Alliance, One World or Skyteam offers a full codeshare agreement between all partner airlines and all routes. The complex structure of codeshare agreements between airline´s around the world, would lead to a massive amount of required data, which are not available in a single database. Hence, to reflect reality inside the simulation, the three major alliances –as mentioned before- are implemented in the simulation. The path finding algorithm is searching for all possible flights inside one alliance. A change of an alliance partner during the itinerary is impossible.

The next heuristic describes possible routings between the different airline-specific airports (hub vs. non-hub) and is shown in the following table.

Case	Origin	Destination	1st stop	2nd stop
1	Hub	Hub	Hub	Not allowed
2	Non-Hub	Hub	Hub	Hub-only on interregional routes
3	Hub	Non-Hub	Hub	Hub-only on interregional routes
4	Non-Hub	Non-Hub	Hub	Hub-only on interregional routes Hub and routes inside North America and North-west Asia

Table 1: Routing specification for path finding algorithm

This routing specification was derived from real booking data, where a specific routing scheme could be observed. The first case is an itinerary between a hub as origin and a hub as destination. In that case, only one stop at another hub is allowed. A second stop is inside the path finding algorithm not allowed. Cases 2 and 3 are representing an itinerary between one non-hub and one hub. In these two cases, the first stop has to be at a hub. This is in line with the first heuristic as mentioned before.

After that, a second stop at a hub is only allowed, if the origin´s region is unequal destination´s region according the OAG´s region definition. The last case describes the routing between two non-hub airports. There, a routing via two hubs is allowed, if origin´s region and destination´s region are unequal or origins and destinations are located inside North America (NA1) and North-west Asia (AS4) due to their large land size. The last heuristic filters possible hubs based on their geographic location.

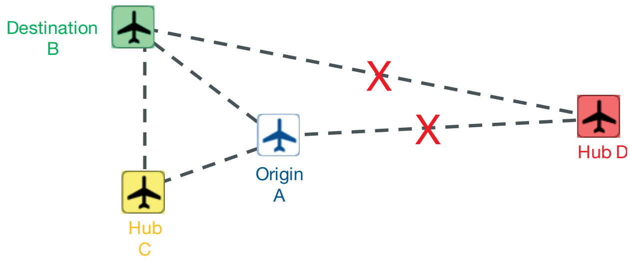

Figure 3: Selection of possible routings based on distance resistances

With this heuristic, only routings are selected which do not exceed a maximum target resistance. As shown in the figure, a routing from A to B via C is allowed, whereas a routing via hub D is excluded. The maximum target resistance was modeled in a distance dependency, with higher values for shorter flights. With these heuristics, the path finding algorithm selects possible routings in a very efficient and fast way. Validation showed that nearly 86% of all real routings were found by the algorithm.

3.2.2. Modelling of air fares

After the determination of all possible routes/itineraries between an origin and destination, air fares have to be determined for these routes. Since the Airline Deregulation Act in 1978, air fares cannot be calculated directly from mathematical expressions. Air fares are strongly linked to passenger demand, competiveness, costs and other issues [30] To derive mathematical functions for air fares, air fares have been queried from an internet-based travel agency and have been analysed later on. [31] could observe a dependency between air fares and OD distance as well as OD region. Hence, air fares are modelled inside the simulation basing on distance and OD region (North America-NA1, Western Europe-Eu1 and North-west Asia-As4). To reflect reality as much as possible, 8 different air fare functions were developed (4 functions representing four booking classes inside the Economy Class, 2 for Business and 2 for First Class air fares). The number of seats per fare class was obtained from [31] and set being constant for a simulation run.

3.3. The evaluation process – Modelling cost functions of flight alternatives

The evaluation of flight alternatives by the decision maker –here a passenger- can be made on an utility-based or cost-based approach. The latter one is used inside the simulation tool. All flight alternatives are assessed by cost functions from flight ticket, flight schedule and operating airline, as shown in the following figure. With the definition of the main three groups of costs for flight alternative´s attributes, on which the passenger is choosing the one with lowest generalised cost, the following chapters deal with the derivation and definition of cost functions.

Figure 4: Generalised costs of a flight alternative as a sum of costs from ticket, schedule and airline

3.4. The evaluation process – Modelling cost functions of flight alternatives

3.4.1. Cost functions of flight schedules

The first group of costs dealing with attributes of the flight schedule and includes costs for departure time, arrival time, properties of stops and total travel time. In the literature, at least two different approaches to evaluate departure and arrival times can be found. The first one was introduced by [32]. This theory says that a passenger has an ideal departure time during a day. The difference in offered departure time by an airline and ideal departure time is called *schedule delay* and results into disutility or costs. The second theory, developed by [33] stated that a passenger does not have an ideal departure time but a window for possible departure times. This model is also called *decision window model*. Every flight within this window does not generate costs or disutility. All flights outside this window will not be considered. The third and newest theory was developed by [34]. This theory is a mix from the two previous theories. It combines the utility from a deviation from an ideal departure time and a decision window. In [34] this window is called *indifference window*, which is zero to three hours wide, depending on traveller type as well as departure or arrival time. A summary of all three theories is shown in the following figure below.

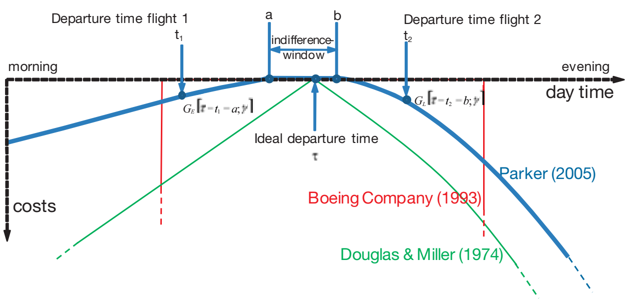

Figure 5: Theories of schedule delay [32],[33],[34]

In the following subchapters, costs functions for departure and arrival time will be setup based on the developed theory from [34].

Departure time

The influence of departure time onto passenger´s booking behaviour has been extensively investigated by various studies. Results can be found by [28],[35],[36],[37],[38],[34]. Whereas [28] and [37] modelled fixed cost functions for departure times during a day for private and business travellers, all other studies derived costs functions depending on deviations from an ideal departure time. This modelling approach needs the knowledge about the distribution of ideal departure time during a day. Distributions can be obtained from [34] or with similar results from [39].

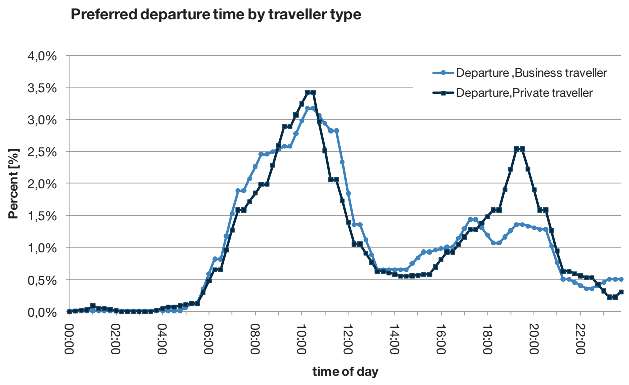

Figure 6: Departure time distribution for time of the day by traveller type [34]

It can be seen that ideal departure time distributions have two peaks during a day. The first peak for both traveller types can be seen between 6am and 12am, the second one between 4pm and 9pm. For business travellers these peaks are wider than for private travellers. This might be explainable due to the manifold reasons of business travels. Private travellers tried to maximise their time at the destination with early departure or late departure one day before. It has to be mentioned that this distributions are preferred departure times, not taken into account higher air fares during these peak hours which reduces the percentage of private travellers during these times. The following figure shows the costs of schedule delay based on [34], for a flight ticket of 500€ as basefare for private and business travellers.

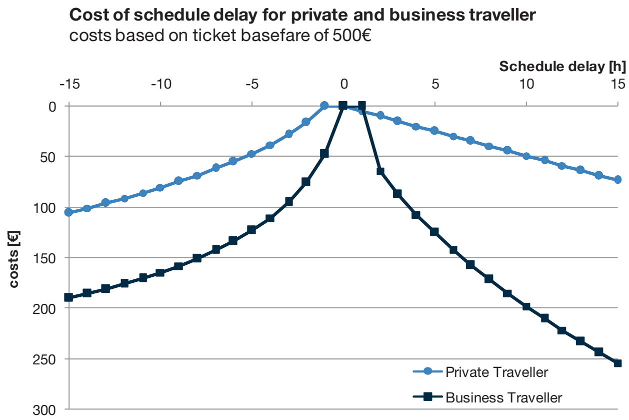

Figure 7: Cost functions for schedule delay of private and business travellers [34]

From that figure, it can be seen that for business travellers higher costs are generated with a deviation from the ideal departure time. The indifference window is 1h wide for both traveller types. The only difference is the location. For business travellers, the window is located one hour after the ideal departure time. The indifference window of private travellers is located one hour before the ideal departure time. With the cost functions and ideal departure time distributions for both traveller types, costs of departure times are determined inside the simulation.

Arrival time

The approach to model costs inside the simulation for arrival times is similar to departure times. Values and distributions are taken from [34] directly. It has to be mentioned that for arrival times, costs functions were only calculated by [34]. No other studies were found dealing with costs of arrival times.

Arrival and departure time sensitivity

In the previous two subchapters, cost functions for departure and arrival times were setup. According to [24] and [39], it could be found that not both times are taken simultaneously into account if evaluating a flight option. There are ODs where departure time is more important than arrival time. A summary of sensitivities is presented in the following table as used inside the simulation.

Private traveller

	Negative O-D time difference	neutral O-D time difference	Positive O-D time difference
Departure time	21.9%	20.1%	18.3%
Arrival time	31.2%	33.1%	35.0%
Both	47.0%	46.8%	46.7%

Business traveller

	Negative O-D time difference	Neutral O-D time difference	Positive O-D time difference
Departure time	20.1%	16.4%	12.9%
Arrival time	31.7%	32.4%	33.0%
Both	48.2%	51.2%	54.1%

Table 2: Time sensitivities for business and private travellers depending on OD local time difference

Both studies showed that private travellers have a stronger preference on departure time. Furthermore, preferences for both traveller types are decreasing if time difference (difference in local time between origin and destination) are positive.

Stops

For the definition of cost functions for one or more stops during itinerary, properties of a stop changes the perceived utility. According to [33], a stop can have three different characteristics. If a stop does not require an aircraft change, this stop is called one-stop connection. If a stop requires an aircraft change, but the connecting flight is operated by the same airline, [33] defines this stop as a single connect. If a stop requires a change of airline and aircraft, this stop is further called interline connect. The same refers to itineraries with more than one stop, then stops are called double connect or double interline.

There are quite a few studies [40],[28],[41],[42] and [43] using logit models to derive cost functions for stops, but these values a mainly constant, not correlating with different passenger characteristics or taking different stop characteristics as mentioned above, into account.

More important studies with a detailed differentiation between passengers and stop properties can be found in [44],[45],[46],[42],[36] and [34]. With these studies, cost functions depending on passenger characteristics (e.g. private travellers, non-reimbursed business traveller or business travellers) and properties of stops (e.g. single/double connect and interline connect) can be derived. Furthermore, cost functions depending on OD distance can be found in [34] and [44]. The simulation started with a mean value from all studies, a cost function for a single connect stop, a private traveller and depending on a base fare was setup. The simulation results showed that mean values out of above mentioned studies for all kinds of stops and traveller types, good correlation of passengers with connecting flights than in reality (compared to DB1B database 4[th] quarter 2004).

Total travel time

Besides departure and arrival time, also total travel time is taken into account by passenger booking choice. In a simplified way, a reduction of travel time by a time unit leads to an increase of willingness to pay (WTP). This WTP is commonly used by expressions like value of time (VOT) or value of travel time savings (VVTS). Similar to cost functions for stops, there are some studies calculating VOT undifferentiated by passenger characteristics. Such studies can be found in [47],[48],[49],[42],[50],[40] and [41]. [45].[34],[26],[36] and [42] calculated values for travel time savings depending on travel purpose. In these studies, values between \$9.96/h and \$23.81/h for private travellers and \$25.76 and \$86.67 for business traveller can be obtained. A more detailed model can be found in [34] The developed model calculates VOT depending on OD distance, travel purpose and relative time savings. These relative time savings lead to non-linear values for VOT. Due to missing information about the final equations for these VOT, mean values from nine studies with a standard deviation of 0.3 [44] are used inside the simulation. VOT for private traveller were set to €15/h and 35€/h for business travellers.

3.4.2. Cost functions of airlines

In passenger´s view, airlines are assessed by their product (onboard and on ground) and their offered service [24]. To determine these manifold properties into cost functions for the simulation, different methods were used. In various studies [44],[40],[26] market presence was one factor for airline choice. Regarding onboard comfort, studies were done by [52] and [34]. Results from these studies were partly difficult to transfer into cost functions, hence another approach was selected.

[44] and [45] calculated costs for favourite and unfavoured airlines in their models. Based on results from [44], cost functions for a favourite airline depending on OD distance were implemented inside the simulation. In the next step, a favourite airline has to be determined for each passenger and OD. For the determination of a favourite airline, an approach from [33] was used and adapted accordingly. In that approach airline image is a part of passenger´s choice criteria. According to that method, airline image is calculated out of four factors (*availability and reliability, marketing programs, service quality* and *passenger environment*) with a weighting depending on OD range. Whereas the needed data to determine the factor availability and reliability are easily to obtain, data for all other three factors are more difficult to receive. This mainly refers to data like properties of food and beverage, seat comfort etc. Therefore, the method was adapted accordingly. In the simulation, the four factors determining airline image were reduced to only two. The first new factor was *availability* and includes properties like number of city served or number of weekly flights. The second one is called *service quality and passenger environment*. In the original approach, values for these four factors can range between one (extremely poor) to seven (excellent) whereas four points meet the standard.

The next step to determine the favourite airline inside the simulation was the definition of values *for service quality* and *passenger environement*. The values for the different airlines were directly obtained from SKYTRAX [53],[54] and [55] where this company assesses airlines in a range from one star to 5 stars. Skytrax is the biggest company in assessing and monitoring airline quality and their results are often used by airlines for marketing Because of the detailed and from experts accepted results from SKYTRAX, these assessment values were used directly as values for *service quality* and *passenger environment* inside the simulation. With the known values for both factors, the original method is further used. With the two factors, a combined airline rating can be calculated. Basing on these values, a coefficient of preference is determined. On the calculated preference, in the final step, a probability of selection of an airline can be calculated. Due to the difference in the service/comfort service (four in the original method, three at SKYTRAX), the function to calculate the coefficient of preference has to be modified accordingly. As mentioned before, the probability of selection is depending on combined rating as well as on all other airlines –precisely on their combined rating- being in the individual passenger´s choice set. With the definition of al probabilities of selection for all airlines inside the choice set, a favourite airline with the costs are determined by a random value inside the simulation.

3.4.3. Cost functions of air tickets

Costs for an air ticket are modelled inside the simulation resulting from the air fare (disutility) and possible costs (utility or negative costs) from frequent flyer programs. Cost functions for the latter one will be explained first.

Frequent flyer program (FFP)

Generally speaking, FFPs generate negative costs. These costs have been identified by various studies like [37],[45] and [42]. [41] and [38] calculated FFP costs depending on passenger type and status inside the program. Both could show that a higher status (e.g. elite status) leads to higher costs (utilities). In the simulation, costs of a FFP is -6€ for private travellers with standard membership and -20€ with an elite status. Costs for Business travellers with standard membership were accounted to -32€ and -80€ for an elite status. The probability of a membership for one FFP is determined inside the simulation by number of undertaken flights per year and directly obtained from [26]. The assignment of a specific FFP for a passenger is done by random numbers basing on an airline´s market share at the origin airport. The status inside a FFP is determined by number of flights per year and also directly taken from [26]. With 20 or more flights per year, passengers are assigned to an elite FFP status.

Ticket fare

The ticket fare (€) is directly used as the cost function for a ticket inside the simulation.

3.5. The choice – Modelling passenger booking behaviour

With the definition of costs based on departure time, arrival time, properties of stops, total travel time, favoured airline ,ticket fare and FFP as well as depending on traveller type, income, travel frequency, age and gender, total costs or generalized costs of all possible flight alternatives inside the individual choice set can be calculated. Based on these generalized costs the alternative with lowest total cost is booked.

4. VALIDATION AND SIMULATION RESULTS

For validating results of PARIS simulations, real booking data from the US were used. Precisely the DB1B 4th quarter 2004 were used because, OAG data were only available for October 2004. Because DB1B coupon database includes 12 weeks but only a sample of 10% of all sold tickets, the number of transported as well as OD passengers were recalculated according to one week. The DB1B database consists of more than 60,000ODs with more than 5 million origin-destination passengers, resulting to 12.5 million transported passengers in one week (first column). Simulating of all ODs inside the US would lead to an extensive computing time. Hence, number of simulated ODs was reduced to only ODs with more than 100 passengers per week. This results into a reduced number of ODs of nearly 1/10 whereas number of OD passengers reduces only by 16% (second column).

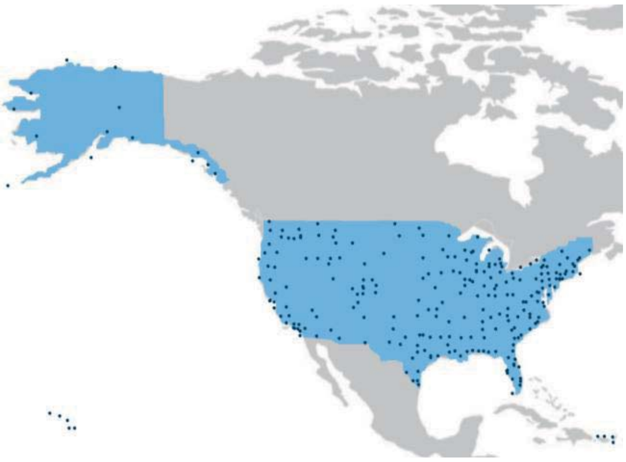

Figure 8: Visualisation of simulated airports in the US with at least one OD with passenger demand of 100PAX per week

The PARIS simulations showed really good aggregate results in terms of simulated ODs, number of OD PAX and number of transported passengers. In the simulation, number of transported passengers is higher compared to DB1B data due to higher percentage of connecting passengers inside PARIS. This results mainly due to the fact that inside PARIS passengers are booking always a return flight. According to DB1B, nearly 20% of all flight coupons, no return flight was booked, or return flights were booked separately.

Comparing the percentages of connecting passengers on routes where direct flights are offered (data extracted from OAG database), PARIS calculated a percentage of 13.9% connecting passengers which is similar to values from $DB1B_{ODPax>=100}$ and DB1B. It can also be seen that percentages of connecting passengers in ODs with offered direct flights in both DB1B databases are not changing significantly. This results in the fact that the ODs which are excluded in the $DB1B_{ODPax>=100}$ database are mainly ODs with connecting flights.

	DB1B 4th Quarter 2004	DB1B 4th Quarter 2004 OD PAX>=100/week	PARIS Simulation
Number of ODs	60668	6342	6342
Number of OD PAX	5,041,651	4,347,337	4,316,571
Number of transported Passengers	12,554,510	10,045,727	10,881,234
Percentage of connecting passengers wrt OD passengers	31.3	23.6	25.2
Percentage of connecting passengers wrt transported passengers on direct markets	13.9	13.9	13.9

Table 3: Overview of simulation results compared to real booking data (DB1B coupon, 4th quarter 2004)

The following figure shows number of transported passengers per airline and the difference between PARIS simulation and $DB1B_{ODPax>=100}$ database. Overall, it can be seen that PARIS calculates valuable results, even if higher passenger number are accounted to some airlines. Higher values for Southwest Airlines (WN) or Delta Airlines (DL) result in the previous mentioned fact, that inside PARIS return flight for all passengers are always assigned. Out of DB1B database, more than 26% of all passengers with no return flight had a ticket from Southwest. For Delta Airlines, 14.5% of all passengers had there no return flights. The implementation into PARIS of no return flights basing on these results would reduce number of transported passengers.

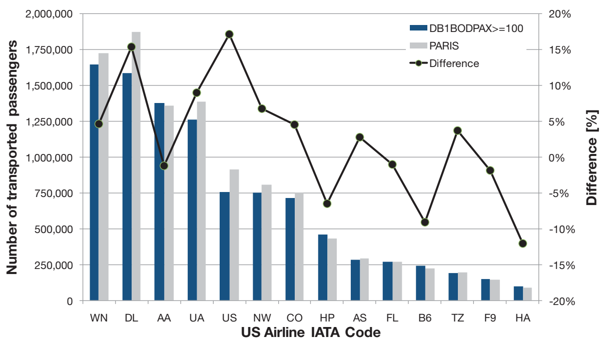

Figure 9: Number of transported passengers and difference between DB1B database and PARIS simulation (all values for one week)

The second possibility for higher values for transported passengers inside PARIS compared to DB1B data is the assignment of some airlines inside OAG to one airline in a frame of codeshares. Even if codeshares were excluded – except for airline alliances- airlines like Skywest Airlines (OO) or Atlantic Coast Airlines (DH) are accounted inside OAG to Delta Airlines (DL), but listed separately inside DB1B. This contribution to overall transported passengers is small but should not be neglected. The last possibility for difference in simulated to real transported passengers lead in the sample size of DB1B. DB1B aggregates passenger numbers for three months with a sample size of nearly 10%. Out of these data, values for transported passengers per week were derived. With this approach errors for airlines with higher transported passengers should be smaller than for smaller airlines. This can also be seen in figure 9, where error is increasing with a decrease of transported passengers.

The last diagram presents the number of connecting passengers depending on US airlines. It can be seen that Southwest (WN) and JetBlue (B6) have the lowest percentage of connecting passengers according to DB1B with less than 20% for WN and 6% for JetBlue. *PARIS* also calculates for these two airlines lower connecting passengers of 21% for Southwest and 2.3% for JetBlue. Except for American West Airlines (HP) and US Airways (US), all other differences range between +/-5%.

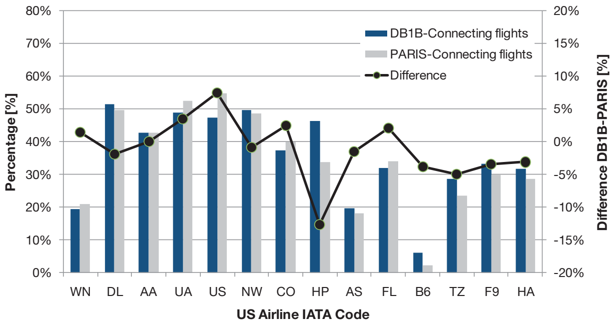

Figure 10: Percentages of connecting passengers for US Airlines, values taken from DB1B and PARIS simulation results

5. CONCLUSION AND OUTLOOK

With setup of cost functions for schedule, ticket and airline properties as well as the segmentation of passengers with respect to socio-demographic and behavioural properties, the presented modelling approach to simulate passenger´s itinerary choice shows first valuable results. Validation showed that not all passengers should be assigned with a return flight. This will reduce number of transported passengers and hence increase accuracy. At this development stage of PARIS, percentages of connecting passengers and number of transported passengers lead to the conclusion that PARIS is capable to simulate today´s commercial air transport system from a passenger´s perspective. Furthermore, with this tool, the effect of introduction of future transport concepts with changed operational issues can be investigated.

References

[1] **ACARE (2002)**. Strategic Research Agenda Volume 1. European Commision, 2002

[2] **Green, J. E. (2005).** Air Travel - Greener by Design. London, United Kingdom: Royal Aeronautical Society

[3] **Green, J. E. (2008).** The scope for reducing the environmental impact of air travel. University of Greenwich, London, United Kingdom: Greener by Design Science and Technology Sub Group

[4] **Egelhofer, R..(2009)** Aircraft Design Driven by Climate Change. München: Verlag Dr. Hut, 2009

[5] **Official Airline Guide (2004)**. OAG Data. October 2004

[6] **Thurston, L. L.(1927)** „A Law of Comparative Judgement." Psychological Review 34,p.273-286

[7] **Luce, D. (1959)**. Individual Choice Behaviour : A theoretical Analysis. New York: Wiley

[8] **Marschak, J.(1959)**. „Binary-Choice Constraints and Random Utility Indicators." In *Mathematical Methods in the Social Sciences*, von Samuel Karlin, Patrick Suppes Kenneth J. Arrow. California: Stanford University Press

[9] **McFadden, D. (1989)** „A method of simulated moments for estimation of discrete response models withouit numerical integration." *Econometrica 57(5)*, 1989: 995-1026

[10] **McFadden, D. (1982)**. *Econometric Analysis of Qualitative Response Models.* Working paper, Cambridge, Massachusetts: MIT Press, 1982.

[11] **Manski, C (1981)**. „Structural Models of Discrete Data." *Sociological Methodology*,p.58-109

[12] **Amemiya, T.(1981)** „Qualitative Response Models: A Survey." *Journal of Economic Literature*,p.1483-1536.

[13] **Ben-Akiva, M. (1985)**. *Discrete Choice Analysis: Theory and Application to Travel Demand.* Cambridge, USA: MIT Press

[14] **Train, K. E. (2003)** *Discrete Choice Methods with Simulation.* Cambridge University Press

[15] **Ben-Akiva, et a**l. (1997) „Modeling Methods for Discrete Choice Analysis." *Marketing Letters*, p.273-286

[16] **Scheidler, M. (2003)**. *Discrete Choice Models for Airline Network Management.* Idstein: Schulz-Kirchner Verlag

[17] **ONS-Office for National Statistics (2005)**. *Travelpac-International Passenger Survey*

[18] **Carrier, E. (2003)**. *Modeling Airline Passenger Choice: Passenger Preference for Schedule in the Passenger Origin-Destination Simulator (PODS).* Master thesis, Boston: Massachusetts Institute of Technology

[19] **Belobaba, P. P. (2006)** *Introduction to PODS Passenger Choice Model.* Lecture notes Airline Management, Boston: Massachusetts Institute of Technology

[20] **Plötner, K. O.(2008)** „Investigation of Long-Haul Flight Attributes Influencing Passenger´s Booking Decision Using SP data." *26th International Congress of the Aeronautical Sciences ICAS*

[21] **Plötner, K. O.(2007)** *Payload Driven Cabin Concepts defined.* NACRE Deliverable D4.2-2 , München: Technische Universität München

[22] **Chin, A. T.H.(2002)**„Impact of Frequent Flyer Programs On The Demand For Air Travel." In *Journal of Air Transportation, Volume 7, No. 2*, p.53-86

[23] **Toh, R.S**.(1988) „Frequent Flier Programs: Passenger Attributes and Attitudes." In *Transportation Journal, Vol.28, Issue 2*, p.11-22. USA

[24] **Doganis, R. (2002)**. *Flying off Course.* London, England: Routledge

[25] **IATA (1998)** *Corporate Air Travel Survey.* Montreal, Kanada: IATA

[26] **Koppelman, F. et. al.(1999)** „The choice of air carrier, flight, and fare class." *Journal of Air Transport Management Vol. 5*,p.193-201

[27] **Mason, K. J.(2002)** „Future Trends in Business Travel Decision Making." In *Journal of Air Transportation, Vol. 7, No. 1*, p.47-68

[28] **van Eggermond, M. A.B (2007)**. „Consumer choice behaviour and strategies of air transportation service providers." In *Master Thesis*. Institute for Transport Planning and Systems, ETH Zürich

[29] **Sterzenbach, R.(1996)**. *Luftverkehr*. München: Oldenbourg Verlag
[30] **Pompl, W. (2002)**. „Luftverkehr.“ Berlin: Springer Verlag
[31] **Meyer, M. (2008)** *Untersuchung bestehender Yield Management Methoden, Tarifsysteme und Preisbildungsmaßnahmen in zivilen Luftverkehrsmärkten.* Semesterarbeit, München: Technische Universität München
[32] **Douglas, G W. (1974)** *Economic Regulation of Domestic Air Transport: Theory and Policy.* Washington D.D, USA: The Brookings Institution
[33] **Boeing Company (1993)**. „Decision Window, Path Preference Methodology, Time Mode.“ Von Boeing Commercial Airplane Group.
[34] **Parker, R. A. (2005)** „Estimating the Utility of Time-of-Day Demand for Airline Schedules.“ In *Transportation Research Board*
[35] **Whitaker, B. (2005)**. „Stated Preference as a Tool to Evaluate Airline Passenger Preferences and Priorities.“ In *Transportation research record,Volume 1915 / 2005*, 55-61. Washington, DC: National Research Council
[36] **Garrow, et al.(2007)**„How much airline customers are willing to pay: An analysis of price-sensitivity in online distribution channels.“ *Journal of Revenue and Pricing Management Vol. 5*, p.271-290
[37] **Carrier, E. (2008)** *Modeling the Choice of an Airline Itinerary and Fare Product Using Booking and Seat Availability Data.* Forschungsbericht, Massachusetts Institute of Technology
[38] **Koppelman, F. S. (2008)**. „Schedule Delay impacts on air-travel itinerary demand.“ *Transportation Research Part B, Volume 42*,p.263-273
[39] **Salecker, R.(2009)** *Bestimmung der Einflüsse von Flugplaneigenschaften auf das Buchungsverhalten von Passagieren im Langstreckenverkehr.* Semesterarbeit, München: Lehrstuhl für Luftfahrttechnik
[40] **Song, W.(2006)**. „Analysis of Aggregate Passenger Routes in Air Travel - An Atlanta based Study.“ In *Southeastern Geographer, Volume 46(1)*, p.139-160
[41] **Hess, S. (2007)** „Posterior analysis of random taste coefficients in air travel behaviour modelling.“ In *Journal of Air Transport Management, Volume 13*, p.203-212
[42] **Hess, S. (2005)**. „Computing willingness-to-pay indicators for air travellers from SP survey data.“ In *9th Air Transport Research Society Word Conference*. Rio de Janeiro, Brasilien
[43] **Laesser, C. (2007)**. „Valuation of direct intercontinetal flights as oposed to non-direct ones-Insights based on a hedonic approach.“ ATRS Conference Paper, Berkeley, USA
[44] **Lee, S. (2000)**. *Modeling Passenger Disutilities in Airline Revenue Management Simulation.* Master Thesis, MIT, Cambridge: Department of Aeronautics and Astronautics
[45] **Bhat, C.(2006)** „Modleing demographic and unobserved heterogenity in air passengers´sensitivity to service attributes in itinerary choice.“ *Transportation Research Board*
[46] **Makoswski, T. (2006)** „Zukunft des Personenluftverkehrs - Flugroutenverkehrs- und wahlprognose.“ In *Dissertation*. Fakultät für Wirtschaftswissenschaften, RWTH Aachen
[47] **Zamparini, L. (2007)** „Meta-Analysis and the Value of Travel Time Savings: A Transatlantic Perspective in Passenger Transport.“ *Journal of Networks and Spatial Economics*, p.377-396
[48] **Algers, D. S.(1996)** „The National Swedish value of time study.“ *Value of time seminar.* PTRC, England, 1996
[49] **Ramjerdi, F.(1997)** „The Norwegian value of time study: some preliminary results.“ Institute of Transport Economics, Oslo, Norwegen, 1997
[50] **EUROCONTROL (2007)**. *Standard Inputs for EUROCONTROL Cost Benefit Analyses-2007 Edition.* EUROCONTROL
[51] **Coldren, G. M.(2003)** „Modeling aggregate air-travel itinerary shares: logit model development at a major US airline.“ In *Journal of Air Transport Management, Volume 9*, p.361-369
[52] **Espino, R. (2006)** „Evaluating the effect of moel specification on willingness-to-pay for service quality.“ In *10th Annual World Conference Air Transport Research Society*. Nagoya, Japan, 2006
[53] ***Skytrax 1 (2009)*** http://www.skytraxresearch.com/General/profile.htm (last call up 11/03/2009).
[54] ***Skytrax 2 (2009)*** http://www.skytraxresearch.com/General/qtp.htm (last call up 11/03/2009).
[55] **Skytrax 3 (2009)** „Airline and Airport reviews.“ Juni 2009. http://www.airlinequality.com/ (last call up 06/062009)
[56] **Widenhorn, S. (2008)**. *Kaufentscheidung im High-Prize-Segement am Beispiel alternativ gestalteter Flugzeug-Innenräume- Eine soziologische Betrachtung der Konsumentscheidung.* Diplomarbeit, München: Ludwig-Maximilians-Universität zu München