MODELLING AIRLINE COMPETITION IN PASSENGER AIR TRANSPORT MARKETS – A GAME-THEORETIC APPROACH

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ABSTRACT

The purpose of this paper is to present a quantitative model of passenger air transport markets. Passenger air transport demand is not a fixed model-exogenous input parameter but is determined model-endogenously and therefore depends among other factors on the supply of flights and their various characteristics. Competitive relationships between airlines are modelled within a game-theoretic framework. The model assumes that airlines have incomplete information about the characteristics of each other (e.g. high-cost vs. low-cost airline). Individual beliefs about the nature of different competitors are adjusted by a dynamic learning process over time.

One of the central objectives of the model is to explain the dynamic developments of air transport markets and their competitive forces, i.e. temporary disequilibria and the long-run market equilibrium. Some interesting questions to examine include e.g. an analysis of entry deterrence strategies of incumbent carriers and market entry strategies of new carriers. In this context incomplete information plays a critical role with regard to the profitability of such strategies and thus influences market developments.

The model is of interest especially with regard to the evaluation of business strategies on the part of airlines and for public institutions that wish to analyse various market scenarios and evaluate politico-economic actions.

1 INTRODUCTION

In recent years, there has been an increasing interest in the modelling of competitive relationships within the passenger air transport markets. The key drivers of this trend were the growing importance of deregulated and thus more competitive passenger air transport markets and the rise of new business models in aviation.

According to the competitive environment of passenger air transport markets, we differentiate between three classes of models: models of monopolistic competition, models of oligopolistic competition (but without extensive network optimisation capabilities and thus only applicable to some problems) and models of oligopolistic competition with extensive network optimisation capabilities, which are therefore applicable to a wider range of problems.

The first class of models serves to optimise flight structures between airports and is largely applied to complex hub-&-spoke systems, where coordination costs tend to be high. Such models include extensive network optimisation capabilities, in order to produce feasible flight schedules as dictated by passenger demand, flight restrictions and capacity constraints. These models are usually applied under monopolistic conditions and examples of such models include Gordon (1974), Jacquemin (2006), Jeng (1987) and Miller (1963). Passenger demand is assumed to be fixed in most models and their aim is to optimise flight structures, in order to meet a certain demand.

The second class of models comprises of models predominantly tailored to analyse a particular question in an oligopolistic market environment: they typically focus on point-to-point traffic and simple hub-&-spoke networks of low complexity, without considering special flight restrictions and capacity constraints. A popular topic is the analysis of market equilibrium and social welfare in deregulated and regulated markets. Examples include Douglas and Miller (1974), Panzar (1979, 1980), Schipper et al. (2003) and Zhang (1996). Further analysis comprises network competition, network invasion and entry deterrence. Pels (2009) considers point-to-point and hub-&-spoke traffic, in order to analyse the effects of network competition between two airlines (with regards to the invading of each other's network).

The third class of model is associated with competitive relationships and includes extensive network optimisation capabilities; however, the members of this class still differ to some degree, in their ability to model market structures and complex network structures. Nevertheless, the ability to include competitive relationships between market actors and more flexible network structures enhance model practicality in a multitude of real-life problems. Models which focus more on (multi-) hub-&-spoke systems, with an exogenously-given passenger demand, are Dobson and Lederer (1993), Kanafani and Ghobrial (1985), Hansen (1990) and Hansen and Kanafani (1990). Evans et al. (2008), Evans and Schäfer (2009) and Adler (2001, 2005) develop models of airline competition which are applicable to a wider range of different network structures and number of competitors.

In this paper we present a model of passenger air transport markets that is not limited to a particular number of airlines and airports or network structures. Demand for passenger air transport is not a fixed model-exogenous input parameter but is determined model-endogenously and therefore depends on, amongst other factors, the supply of flights and their various characteristics. Competitive relationships between airlines and airports are modelled on a game-theoretic framework and there are three major innovations, when compared to existing approaches: the method of modelling air passenger demand, the handling of incomplete information and learning and how market equilibrium is computed.

One of the central objectives of the model is to explain the dynamic developments of air transport markets and their competitive forces. In this context, incomplete information and learning play a critical role, with regards to the profitability of deterrence and entry strategies.

2 METHODOGICAL BACKGROUND

2.1 Game theory

A game-theoretic model comprises a finite set of N players, for each player *i* a nonempty action set A_i with elements a_i and a preference relation $\succsim_i$ on the set of action profiles $a = \left(a_j\right)_{j \in N}$. The set of action profiles is denoted $A = \times_{j \in N} A_j$ (Osborne and Rubinstein, 1994). The most popular solution concept employed in game theory is that of Nash equilibrium (Nash, 1951). A Nash equilibrium can briefly be described as an action profile in which each player's action is a best response, given the actions of the other players, and thus no player can profitably deviate. More formally, a Nash equilibrium of a strategic game $\langle N, (A_i), (\succsim_i) \rangle$ is a profile $a^* \in A$ of actions with the property that for every player $i \in N$ we have $\left(a_{-i}^*, a_i^*\right) \succsim_i \left(a_{-i}^*, a_i\right)$ for all $a_i \in A_i$. Here, a_{-i} describes an action profile exclusive of the action of player *i*: each player is assumed to have complete information about the relevant characteristics of the strategic game and thus acts rationally (Osborne and Rubinstein, 1994). In a repeated game, the so-called stage game is played in each of the periods $t \in \{0, 1, \ldots\}$. A player's choice in the stage game is denoted as an 'action', whilst their behaviour in the repeated game is termed a 'strategy'. In this paper, we look at repeated games of perfect monitoring; i.e. that all players observe the chosen action profile at the end of each period (Mailath and Samuelson, 2006).

Strategy games are dominated by equilibrium analysis; however, in many cases, the assumptions that players immediately and unerringly identify and play an equilibrium strategy, thus the equilibrium being common knowledge (Aumann, 1976; Milgrom, 1981) to the players, may be questionable (Milgrom and Roberts, 1991). Learning dynamics become even more important if players acquire new decision-relevant information in the course of play, which is typical if the same or a similar game is repeated several times. Fictitious play (Brown, 1951; Robinson, 1951) is such a learning rule: every player is assumed to choose a best response to the assessed strategies of his opponents in every period of the game while he believes that his opponents are playing a mixed strategy, which is given by the empirical distribution of their past actions. The essential idea behind this approach is that, at least asymptotically, past choices of opponents serve, to some extent, as a sound guide to their future behaviour (Fudenberg and Kreps, 1993). Smooth fictitious play was first analysed by Fudenberg and Kreps (1993): in this, players choose a perturbed version of their best response, but perturbation diminishes as the game progresses. The random utility model is one of the reasons for employing smooth fictitious play: players choose to randomise, even when they are not indifferent between their actions, as a means of protection from mistakes in their model of opponent's play (Fudenberg and Levine, 1998).

2.2 Discrete choice theory

The fundamental hypothesis of discrete choice models is the assumption of individual utility maximisation. However, from an outside perspective, the utility of an alternative for a specific individual represents a random variable. Thus, utility U_i for alternative *i* is decomposed into a deterministic component V_i and a random component ε_i (McFadden, 1974):

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

Hence, from an external point of view, only evidence in terms of the probability of an alternative being the one with the highest utility is possible. The most prominent member is the logit-model, with independently and identically distributed random components. The choice probability of an alternative *i* is computed as (McFadden, 1974):

(2) $$P_i = \frac{e^{\mu U_i}}{\sum_j e^{\mu U_j}}$$

3 MODEL

3.1 One-period decision problem

General Notation

C^{ac}_{atijm}	Other variable aircraft costs of airline *a* in period *t* on flight route *i*→j for aircraft of type *m*
C^{P}_{atiklj}	Other variable passenger costs of airline *a* in period *t* on flight route *i*→*k*→*l*→*j*
f_{atijkl}	Flight frequency offered by airline *a* in period *t* on flight route *i*→*k*→*l*→*j*
G_{ai}	Set of airlines which take precedence over airline *a* at airport *i*
P_{atiklj}	Airline's *a* ticket price in period *t* for flight route *i*→*k*→*l*→*j*
P^{f}_{it}	Full passenger charges for departing passengers at airport *i* in period *t*
P^{t}_{it}	Transfer passenger charges for stopover passengers at airport *i* in period *t*
P^{l}_{itm}	Landing charges at airport *i* in period *t* for aircraft of type *m*
$P_{atikljn}$	Probability of *n* competitors being active on flight route *i*→*k*→*l*→*j* in period *t,* from the viewpoint of airline *a*

$q_{atikljn}$	Element *n* of the vector of service quality variables for flight route *i→k→l→j* of airline *a* in period *t*
S_{aijm}	Seat capacity of aircraft of type *m* of airline *a,* operating on flight leg *i→j*
S_{tiklj}	Number of competitors on flight route *i→k→l→j* in period *t*
V	Set of feasible combinations of *i*, *k*, *l* and *j*
x_{atiklj}	Number of seats offered by airline *a* in period *t* on flight route *i→k→l→j*
y_{atijm}	Number of aircraft of type *m* of airline *a* operating on flight leg *i→j* in period *t*
z_{it}^{r}	Runway capacity supplied at airport *i* in period *t*
z_{it}^{t}	Terminal capacity supplied at airport *i* in period *t*
$\alpha_{atikljn}$	Coefficient *n* of inverse demand function P_{atiklj}
$\Delta^{atmopn} x_{btiklj}$	Airline *b*'s increase of number of seats supplied on flight route *i→k→l→j* in period *t,* if airline *a* increases her number of seats offered on flight route *m→o→p→n* in period *t* by one unit
$\Delta^{atmopn} x_{b(t+1)iklj}^{t}$	Prediction of $\Delta^{atmopn} x_{b(t+1)iklj}$ in period *t* for period *(t+1)*
$\pi_{atikljn}$	Profit of airline *a* in period *t* on flight route *i→k→l→j* with *n* airlines being active

Airlines

In this section, we present the one-period decision problem for each airline; i.e. one-period profit-maximisation. In this, each airline views the values of the strategic decision variables of competing airlines as input data for their decision process.

(3) $$Max\ \pi_{at}^{al}\left(x_{at}, y_{at}\right) = \sum_{\substack{i,k,l,j \\ i\neq j, j\neq k, k\neq l, \\ i\neq k, j\neq l, i\neq l}} \left(\left(P_{atiklj}\left(\ldots\right) - C_{atiklj}^{p} - P_{it}^{f}\left(z^{t}\right) - P_{kt}^{t}\left(z^{t}\right) - P_{lt}^{t}\left(z^{t}\right)\right) * x_{atiklj}\right)$$

(4) $$+\sum_{\substack{i,k,j \\ i\neq k, \\ k\neq j, i\neq j}} \left(\left(P_{atikkj}\left(\ldots\right) - C_{atikkj}^{p} - P_{it}^{f}\left(z^{t}\right) - P_{kt}^{t}\left(z^{t}\right)\right) * x_{atikkj}\right)$$

(5) $$+\sum_{\substack{i,j \\ i\neq j}} \left(\left(P_{atiijj}\left(\ldots\right) - C_{atiijj}^{p} - P_{it}^{f}\left(z^{t}\right)\right) * x_{atiijj}\right)$$

(6) $$-\sum_{\substack{i,j,m \\ i\neq j}} \left(C_{atijm}^{ac} + P_{jtm}^{l}\left(z^{r}\right)\right) * y_{atijm}$$

Subject to:

(7) $$\sum_{\substack{k,l \\ i\neq j, k\neq l, \\ i\neq l}} \left(x_{atijkl} + x_{atkijl} + x_{atklij}\right) \leq \sum_{m} S_{aijm} * y_{atijm} \quad \forall i, j$$

(8) $$y_{atijm} = y_{atjim} \quad \forall i, j, m; i \neq j$$

(9) $$2 * \sum_{\substack{a \in G \cup \{a\}, j, m \\ i \neq j}} F_{mi} * y_{atjim} \leq z_{it}^{r} \quad \forall i$$

(10) $$\sum_{\substack{a \in G_{ai} \cup \{a\}, k, l, j \\ i \neq j, j \neq k, k \neq l, \\ i \neq k, j \neq l, i \neq l}} \left(2 * \left(x_{atkijl} + x_{atkjil}\right) + x_{atikjl} + x_{atklji}\right)$$
$$+ \sum_{\substack{a \in G_{ai} \cup \{a\}, k, l \\ i \neq k, k \neq l, \\ i \neq l}} \left(2 * x_{atkiil} + x_{atikkl} + x_{atklli}\right) + \sum_{\substack{a \in G_{ai} \cup \{a\}, j, d \\ i \neq j}} \left(x_{atiijj} + x_{atjjii}\right) \leq z_{it}^{t} \quad \forall i$$

(11) $$\sum_{m} y_{atijm} \geq f_{atijkl} \quad \forall i, k, l, j \quad i \neq j, i \neq k, i \neq l$$

(12) $$\sum_{m} y_{atijm} \geq f_{atkijl} \quad \forall i, k, l, j \quad i \neq j, k \neq l$$

(13) $$\sum_{m} y_{atijm} \geq f_{aklij} \quad \forall i, k, l, j \quad i \neq j, i \neq k, j \neq k, j \neq l$$

(14) $$x_{atiklj} \geq 0 \quad \forall i, k, l, j,$$
$$y_{atijm} \in N \cup 0 \quad \forall i, j, m$$

Rows (3) to (6) describe the one-period objective function of each airline. Passenger costs are subdivided into passenger charges paid by the airline to the airport and other variable passenger costs. Like Adler and Berechman (2001), we have subdivided airport charges into passenger charges paid to the departure airport for each passenger carried and landing charges paid to the arrival airport, based on aircraft type and size. Passenger charges are further subdivided into full price, paid to the first departure airport, and transfer price, which is paid at each subsequent hub, if the flight route to the chosen destination of a passenger includes at least one stopover. This airport charges schedule is clearly arranged but also offers enough flexibility to include other relevant charges, such as handling, night and noise charges. The demand function and the inverse demand function $P^{a}(\ldots)$, respectively, are defined for each particular flight route. (…) represents the independent variables of the inverse demand function. Thus, row (3) applies to flights with two stopovers, row (4) corresponds to flights with one stopover and row (5) relates to nonstop flights. Row (6) describes the fixed costs of each flight, composed of aircraft operating costs and landing charges at the arriving airport.

Constraint (7) ensures that aircraft capacity restrictions are fulfilled on each flight leg, whilst constraint (8) balances the number of aircrafts in both directions between two airports, in order to support subsequent tactical and operational network planning (Jacquemin, 2006). Constraint (9) limits the available runway capacity at each airport. The sigma sign includes airline *a* and all competing airlines that take precedence over airline *a*; for example, because of grandfather rules. Each aircraft uses the runway of an airport for arrival and departure, whilst F_{mi} allows for different levels of runway capacity consumption, depending on aircraft type and airport. Constraint (10) limits each airport's terminal capacity available to each airline for flight routes with two, one and no stopovers. Transfer passengers use the terminal for arrival and departure, whereas passengers emplaned and deplaned use the terminal only once. Rows (11) to (13) require the number of flights between two airports to be above the corresponding flight frequency of the corresponding inverse demand function. (14) describes the domain of the strategic decision variables.

Air passengers

Passengers' air travel demand is modelled for each combination of airline and flight route. The demand function approach in this paper is based on the full price demand model (De Vany, 1974; Oum et al., 1995; Panzar, 1979) and the product characteristics approach by Lancaster (1966). The demand a carrier attracts on a specific flight route depends on the number of seats offered and quality of service provided and this also applies to flights that serve as a substitute; however, the degree of substitution may vary, depending on the quality of service supplied. As airlines are modelled as Counot competitors and thus the number of flights and seats provided represent their strategic decision variables, we work directly with the inverse demand function, which we define as follows:

(15) $$P_{atiklj} = \alpha_{atiklj1} - \alpha_{atiklj2} * \sum_{\substack{b, \\ mopn \in V}} \beta_{btmopn}^{atiklj} * x_{btmopn} + \sum_{n>2} \alpha_{atikljn} * q_{atikljn}$$

The last sum in (15) is the weighted sum of the service quality attributes of a particular route, which describes the preferences of air passengers. The coefficient β_{btiklj}^{atiklj} serves as a measure of homogeneity and is therefore defined for values between zero and one. The closer the value approaches one, the more passengers view two flight routes as almost perfect substitutes. In turn, similarity between two flight routes depends on the Euclidean distance between their characteristics; thus, β_{btiklj}^{atiklj} is defined as:

(16) $$\beta_{btmopn}^{atiklj} = \frac{1}{1 + \sqrt{\sum_{n>2} \alpha_{atikljn} * \left(q_{btmopnn} - q_{atikljn} \right)^2}}$$

3.2 Modelling market dynamics

Empirical reaction function and learning dynamics

Competitors' responses to own actions are not assessed through introspection; i.e., by taking the role of each competitor, solving their optimisation problems (including all interdependencies between competitors), analytically deriving their best response function and inserting them into their own decision problem, which is then solved. Such an approach would, in a number of cases, be computationally intractable for problems of a modest size and, moreover, it assumes that players are perfect rational individuals with almost unlimited computing abilities. Thus, the approach adopted in this paper means a partial departure from assuming perfect rational individuals with unlimited computing abilities towards a behaviour based on observed actions of opponents: each airline directly assesses competitors' reactions by means of a so-called empirical reaction function (ERF) to approximate individual behaviour locally:

(17) $$x_{btiklj} = Max\left\{x_{b(t-1)iklj} + \Delta^{atmopn} x_{btiklj} * \left(x_{atmopn} - x_{a(t-1)mopn}\right); 0\right\} \quad \forall b \neq a; mopn, iklj \in V$$

Rosenthal (1981) suggests, in his paper, resorting to the paradigm of decision analysis and assessing each competitor's response directly, instead of a complex game-theoretic analysis. However, Kreps and Wilson (1982) observe the ad-hoc assessment of competitors' behaviour in the approach of Rosenthal, but we build on observed past behaviour: every competitor is assumed to have some initial conjecture about the reactions of his fellow competitors, which is then updated each period by exponential smoothing (the same applies for flight frequency):

(18) $$\Delta^{atmopn} x^{t}_{b(t+1)iklj} = \left(1-\delta\right) * \Delta^{atmopn} x^{t-1}_{btiklj} + \delta * \Delta^{atmopn} x_{btiklj} \quad \forall b; mopn, iklj \in V$$

The parameter δ is bound between zero and one: the more δ approaches a value of one, the more recent observations have an influence on future conjectures.

Exponential smoothing allows accounting for noise in the data, as $\Delta^{atmopn} x_{btiklj}$ itself is a random observation. An ERF based on exponential smoothing lends more weight to recent observations than past ones, as opposed to 'pure' fictitious play, which Milgrom and Roberts (1991) criticise because it puts equal weights on each observation, no matter how distant they are. More recent observations are often assumed be a better guide to future behaviour than distant observations. Furthermore, the exponential smoothing mechanism has a similar effect as smooth fictitious play (Fudenberg and Levine, 1998) and accounts for the stochastic nature of opponents' actual behaviour observed each period: here, randomisation serves as a means of protection from mistakes in one's own model of opponent's play.

To conclude, from the point of a particular airline, their competitors are fully described by their ERFs. Competing airlines are subdivided into real airlines and virtual airlines; each of these may be further subdivided according to airline types: for example, full service network carrier and low-cost carrier. Real airlines are those that actually compete in a market, whereas virtual airlines do not currently compete in a market but may do so in the future. Real airlines are updated solely on the basis of their own observed behaviour, whereas virtual airlines are updated on the basis of the average observed behaviour of airlines of their type.

Market entry/exit probability function

Market entry and exit is modelled as a choice of 'nature' and thus a chance event from the point of view of the individual market actor; however, this choice depends, to some degree, on own behaviour. Typically, market profitability is raised in the search of relevant variables that have a major impact on the future number of participants in a market: the higher the market profits, the higher the probability that market actors stay in the market or that even new entrants are attracted and vice-versa. However, average market profitability is not very operational, from the point of view of a single market actor, as opponents' market profits and thus average market profits are usually not really observable to them; thus, as competitors' market profits tend to be positively correlated, we choose the proxy variable 'individual market profit' as a guide to future market structure from the point of view of each individual competitor. Hence, every market actor estimates market-specific relationships between the probability of meeting a particular number of next period market participants and his own current market profits:

(19) $$P_{atikljn} = \frac{e^{U_{atikljn}}}{\sum_{m} e^{U_{atikljm}}} \quad \forall iklj \in V$$

(20) $$U_{atikljn} = \phi_{atiklj1} + \phi_{atiklj2} * \pi_{a(t-1)ikljn} \quad \forall iklj \in V; \phi_{atiklj2} \geq 0$$

The profits in (20) are assumed to result from rational and profit-maximising behaviour, in order to serve as an indicator for future market entry and exit. Thus, the cost of deterring entry or promoting exit differs by airline characteristics, depending on whether a competitor is weak or strong, which is reflected in their parameters of (20).

Heuristic equilibrium concept

Figure 1 illustrates a stochastic infinite horizon decision problem of a particular airline, where markets are defined by flight routes *i→k→l→j*. Different markets are connected by the passengers' inverse demand functions and ERFs. Circles represent states $S_{tiklj} = n$ and describe a single period decision problem of an airline for period *t* in market *i→k→l→j,* given a fixed number *n* of competitors. Typically, only few airlines compete on a particular flight route and thus the maximum value of *n* is rather small. At the beginning of the planning cycle, airlines adjust their strategic variables for each period, in order to maximise their expected net present value: they consider any new information they may have learned up to the current period. Different states are distinguished by a time index *t* and a number *n* of competing airlines with certain decision-relevant characteristics. Arrows between circles describe transition probabilities $P_{atikljn}$ (MEEPs) between states.

A dynamic stochastic programme of a size to model real-world problems is typically manageable if it comprises only two to three periods. The complexity of the decision problem depicted in Figure 1 grows quickly with each period added and is already barely manageable if the number of periods exceeds three for realistic sized problems. However, simply cutting off the problem after a certain number of periods is not an adequate solution, due to reputational effects: each airline tends to have an incentive to behave more aggressively in earlier periods, in order to encounter less competition in later periods and reap the rewards of such a strategy. If there is an artificially created last period, airlines have no more incentive to maintain their reputation beyond that period, which they then, possibly, 'milk'.

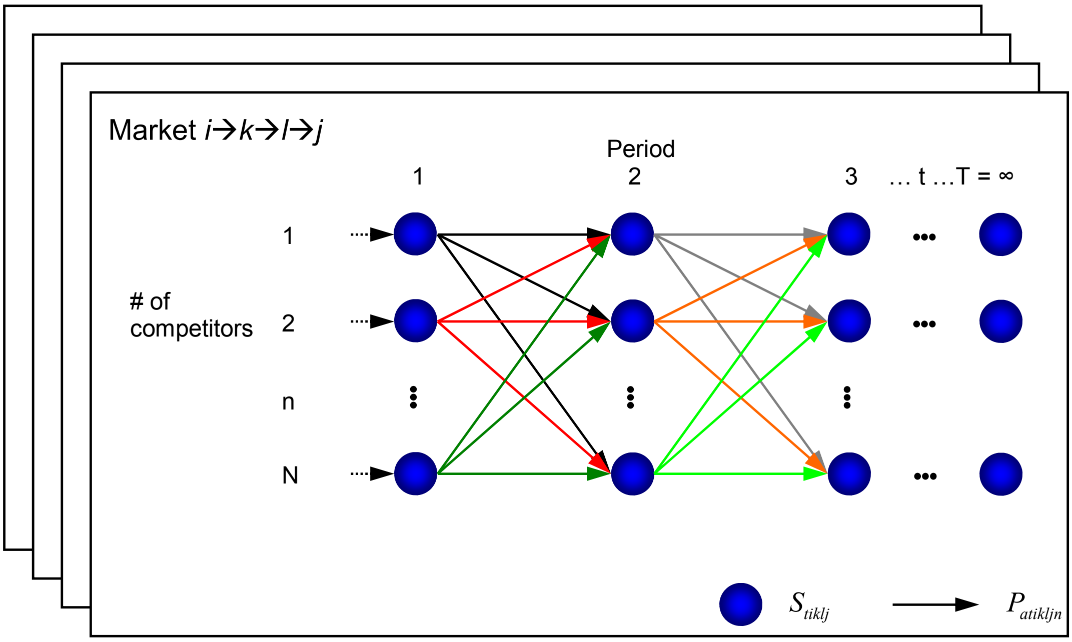

Figure 1: Strategic decision problem of an airline

The background for finding a sound approximation is Bellman's equation (e.g., Powell, 2007):

(21) $$x_t^*(S_t) = \max_{x_t}\left(\pi_t(S_t, x_t) + \frac{1}{1+i} * V_{t+1}(S_{t+1})\right)$$

Here, x_t represents the decision in period *t*, π_t is the one-period contribution, *i* is a discount factor and $V_{t+1}(S_{t+1})$ describes the value of landing in state S_{t+1} in period *(t+1)*. We subsequently denote the one-period contribution as short-term profit (STP) and the discounted value of landing in a particular state as long-term profit (LTP). One-period contribution and the discounted value of landing in a state are both modelled as two-period games, in order to allow for reputational effects between two adjacent periods. The discounted value of landing in a state is modelled as the Nash equilibrium of an infinitely repeated game with discounted payoffs: the repetition of stage game Nash equilibrium in every period is also equal to a Nash equilibrium of the repeated game (Mailath and Samuelson, 2006). As a side constraint, we require the strategic decisions to be equal in both periods. Figure 2 and Figure 3 illustrate the modelling approach.

The LTP decision problem consists only of virtual airlines as its purpose is to model the long-term strategic position of an airline in competition. To link the STP decision problem with the LTP decision problem, we require each airline's decision in the last period of the STP decision problem (period 2) and the first period of the LTP decision problem (period *t*) to be identical, thus preventing reputation milking in the last period of the STP decision problem.

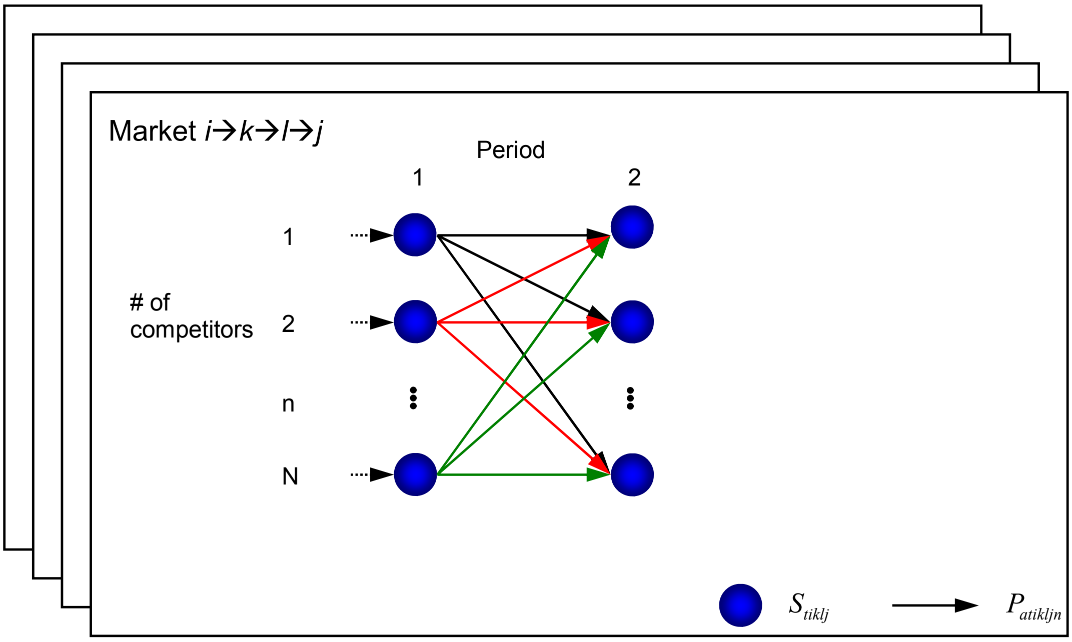

Figure 2: Modelling airlines' short-term payoffs

Thus, the STP decision problem of an airline *a* is represented as:

(22) $$Max\ \pi_a^{stp}\left(x_a, y_a\right) = \sum_{iklj \in V, n, m} \left(P_{a1ikljn} * \left(\pi_{a1ikljn} + \frac{1}{1+i} * P_{a2ikljm} * \pi_{a2ikljm} \right) \right)$$

Subject to: (7) – (14)

(23) $$x_{a2} = x_{at} \quad \forall t > 2$$

The LTP decision problem of an airline *a* is defined as:

(24) $$Max\ \pi_a^{ltp}\left(x_a, y_a\right) = \frac{1}{i\left(1+i\right)^2} \sum_{iklj \in V, n, m} \left(P_{atikljn} * \left(\pi_{atikljn} + \frac{1}{1+i} * P_{a(t+1)ikljm} * \pi_{a(t+1)ikljm} \right) \right)$$

Subject to: (7) – (14) and (23)

Here, $P_{atikljn}$ represent initial state probabilities in period *t*. They are initialised by some estimates; for example, on the basis of the STP decision problem and they are updated during each new planning cycle, according to the observed frequencies of the actual number of competitors in each period through exponential smoothing. The complete decision problem of an airline to approximate the net present value maximisation consists of the sum of (22) and (24), subject to (7) – (14) and (23). There are, essentially, only two different periods for which decisions are to be made, as we require decisions of period 2, *t* and *(t+1)* to be identical. This drastically reduces the number of strategic decision variables and thus model complexity, compared to a case with different decisions for each period in an (infinity) horizon decision problem.

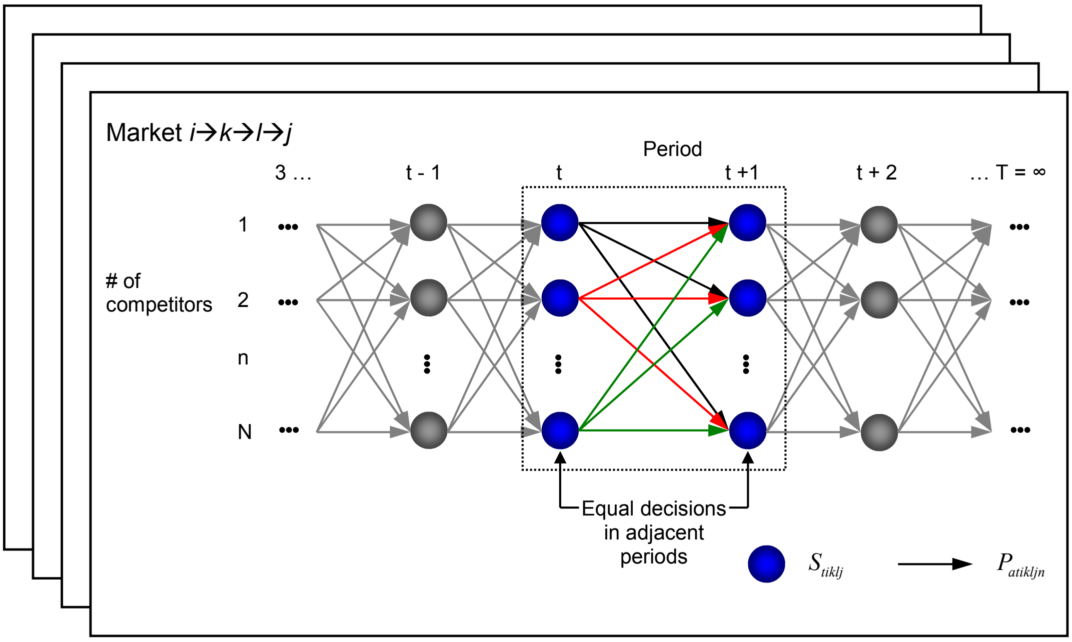

Figure 3: Modelling airlines' long-term payoffs

4 SUMMARY AND CONCLUSIONS

In this paper, we have presented an approach to model airline competition. We assume that airlines maximise their profits and air passengers maximise their utility and, compared to related models that mainly focus on equilibrium analysis, this model is primarily aimed at explaining temporal market developments and learning effects, in which equilibrium is not indispensable. The approach we have chosen is a mixture of decision theory and game theory: we introduce the concepts of a so-called empirical reaction function and market entry/exit probability function, in order to model opponents' reactions on own actions and the market entry and exit of competitors. An essential element of this approach is that airlines learn about the behaviour of their competitors over time on the basis of observed past actions. They calculate the benefits of their own market entry, in addition to entry deterrence and market exit of competitors. However, these issues substantially increase model complexity and, therefore, a heuristic equilibrium concept is presented, in order to find a sound approximate model solution for each period.

In the context of market entry and entry deterrence, Selten's chain store paradox (Selten, 1978) has received much attention: in a multi-period game, with perfect information about each other's payoffs, entry deterrence is not a perfect equilibrium and thus not rational. The key factor driving this conclusion is that it is common knowledge (Aumann, 1976; Milgrom, 1981) that accommodation is the best response to entry and vice-versa. Therefore, reputational effects play no role in this model (Milgrom and Roberts, 1982). However, Kreps and Wilson (1981) note that the common knowledge assumption regarding the monopolist's payoff is very strong in real-life contexts.

The models of Kreps and Wilson (1982) and Milgrom and Roberts (1982) attempt to explain Selten's chain-store paradox, by introducing incomplete information about the nature of the incumbent into the game.

Kreps and Wilson introduce a small probability p that, at any given stage of the game, a predatory response is directly more profitable for the incumbent than sharing the market. Information about actual payoffs of the incumbent is incomplete from the point of view of an entrant, which is an important difference to Selten's model. Probability p is updated each round, on the basis of observed behaviour. However, the results of the model depend on choosing the nature of p and thus the information of the entrants about the payoffs of the incumbent which is, to some degree, an ad-hoc assumption.

In the Milgrom and Roberts model, there is incomplete information about the nature of the incumbent: There is, in each case, a small probability that the incumbent always reacts aggressively and cooperatively, when market entry occurs. These two probabilities reflect the doubts that entrants have, regarding whether their modelling of the incumbent's behaviour is correct.

In our approach, each player's incomplete information about the nature of his opponents is modelled by means of ERFs, which are updated each period on the basis of observed behaviour, and MEEPs. In the models of Kreps and Wilson and Milgrom and Roberts, the probability of entry deterrence by the incumbent depends on the entire history of the game and, once the incumbent has failed to prey, future preying has no effect and entry occurs. However, in this paper, whether market entry occurs or not in a particular period depends solely on the state and the decisions of the players of the previous period, rather than on the complete history. If cooperative behaviour has occurred in the past (maybe as a 'mistake', as players have only incomplete information and limited rationality), entry deterrence is still possible in the future. Here, players' information structure is founded on observed past behaviour (→ ERFs) and econometric functions (→ MEEPs).

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