Recent developments in demand forecasting for airline revenue management

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Abstract: Revenue management for airlines strives to maximise revenue as the sum of fares earned through customer bookings. Since the internet enables customers to make more informed choices and low-cost carriers introduced the concept of restriction-free fares, forecasting for airline revenue management has faced new challenges. In addition, advances in dynamic pricing allow for a more sophisticated approach to pricing, but also ask for more information on customer reactions. This paper summarises recent developments in demand forecasting with regard to the prediction of demand in the airline industry. A classification by demand arrival, level, detruncation and behaviour is applied.

Keywords: airline revenue management; demand models; forecasting; revenue; simulation.

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focuses on a concept of evaluating demand forecasts for airline revenue management.

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1 Introduction

Revenue management according to standard books such as Cross (1997) and Talluri and van Ryzin (2004b) is the art of 'selling the right seats to the right customers at the right prices' (American Airlines (1987, as cited in Smith et al. (1992))). For airlines, revenue is calculated as the sum of fares earned through bookings. Optimising the seat allocation for flights has a history that goes back to 1950, but it has dramatically gained in importance with the Airline Deregulation Act of 1978. Since then, the focus has shifted from a leg-based view to network-wide optimisation and from a model of independent demand for separate booking classes to one including correlation (see also McGill and van Ryzin, 1999).

Forecasting demand is one of the fundamental elements of revenue management. Knowledge of the amount and the qualities of demand for seats on any given flight is crucial in order to provide input for a successful model for optimisation. Further research such as presented in Pölt (1998) shows that increases in forecast accuracy result in increases in revenue. This has also been confirmed in Weatherford and Belobaba (2002).

A succinct and fitting description of the demand model needed for revenue management is offered by van Ryzin (2005):

> "[...] it is really the entire system for estimating demand and market response – the data sources, the information technology for collecting and storing data, the various statistical estimations models and algorithms used to process and analyse these data and the infrastructure for deploying model outputs – in short, everything that is required to turn raw data into actionable market information. This is normally called the 'forecasting system' in traditional RM parlance, though forecasting is merely one of its many functions."

With customers having ever more possibilities of matching and comparing prices on the internet (Boyd, 2004) and getting used to the idea of restriction-free fares (Boyd and Kallesen, 2004), forecasting has become more complex in the last decades. At the same time, a more automated approach to revenue management, growing data management opportunities and the resulting need for higher quality forecasts made forecasting methods of ever more interest (see e.g. Chiang et al., 2007; Nason, 2007; Zaki, 2000).

The most important research with regard to demand forecasting for revenue management up to 1999 has been outlined in McGill and van Ryzin (1999). More information, especially on general theory, is provided by Talluri and van Ryzin (2004b). One of the latest overview papers, Chiang et al. (2007), mostly concentrates on applications for revenue management. Other papers such as Weatherford and Bodily (1992), Bitran and Caldentey (2003) and Boyd and Bilegan (2003) focus on other areas of revenue management such as the development of a typology, pricing and the implications of electronic-commerce.

No systematic overview of forecasting research conducted and published in the new millennium has been compiled so far. While this might not seem like a long period, the quickening pace of development especially with regard to dynamic pricing and market-sensitive customer behaviour leads to a growing body of literature. As this is true even when forecasting for the optimisation of overbooking policies is considered, techniques of predicting no-shows and cancellations will not be included here.

In order to provide a thorough overview of forecasting for revenue optimisation, a classification of forecasting research has been developed. Research is divided up by the characteristics of demand that it considers. Four characteristics of demand will be discussed and approaches to forecast them will be outlined:

- *Demand arrival*: the distribution of passenger requests for tickets in the diverse booking classes over the course of the sales period for specific flights or itineraries (travel paths between origin and destination).
- *Demand volume*: the calculation of the development of overall demand over the course of months and years.
- *Demand behaviour*: the reaction of customers requesting tickets to the alternatives that they are offered by the airline and its competitors.
- *Demand detruncation*: the task of deducting the actual demand from observed sales data. This aspect of forecasting influences the previously mentioned ones as it provides the data basis from which estimates about trends or sensitivities are drawn.

2 Demand arrival

Given a fixed overall demand (regarded as the state space according to a terminology derived from Lee (1990)), the knowledge of the exact build up of demand throughout the time during which seats for a flight are sold (*reservation phase, booking horizon*) as well as the sequence of high- and low-fare demand may be used to determine which combination of prices and restrictions should be offered throughout this time. First, distributions that describe demand arrival for a single fare class on a single leg are given in Beckmann and Bobkowski (1958). The resulting description of demand can be referred to as booking curve. In addition to the positive impact of accepted passenger requests, cancellations have a negative impact on this curve. While methods like the one outlined in Beckmann and Bobkowski (1958) provide clear distributions to use in the further optimisation of revenue, they make assumptions about demand arrival that may no longer be valid.

In order to reduce complexity, it is common to divide the reservation phase up and to then observe bookings as they occurred in any of the time slices (*data collection points*).

Any method that considers only those bookings that have already taken place for the flight in question is referred to as *advanced bookings method* according to Lee (1990).

Those concepts that only refer to observed demand on other departures of the same flight numbers are regarded as *historical booking methods*. It is noted that methods combined from both concepts tend to work best – accordingly, most of the current research uses information both from past flights and current bookings.

Poisson processes as a special case of *Markovian processes* are a common way of modelling demand arrival. As they assume that the state of the system they model is only influenced by the latest event, the arrival of demand is regarded as not influenced by booking controls. Customers request tickets exactly once and do not return later if their request is denied. Recent examples of the application of Poisson processes can be found in Talluri and van Ryzin (2004a) and Walczak and Brumelle (2007). The arrival rate of the customers is regarded as a parameter to be estimated either via ad hoc or time series methods or by analysing influence factors as described in Section 4. Once more, the advantage of such methods lies in their formality and thereby in the ease of subsequent treatment. Their limitation lies within the assumption of independent demand arrival.

In order to optimally allocate seats at any point of time within the booking period, Chen et al. (2003) proposed a method of statistical learning that estimates a market value for tickets being purchased at a specific time. This paper thereby extends a model based on a *discrete-time Markov decision problem* in Lautenbacher and Stidham (1999) to the network level. Instead of explicitly forecasting demand, value functions for remaining seats are estimated and updated. This concept offers the opportunity of already considering a certain degree of demand behaviour when estimating demand arrival. However, it does not allow for customers to choose between different itineraries based on the current availability situation.

A similar topic, demand learning for dynamic pricing, is taken up in Xu and Hopp (2005a). This paper includes the assumption of a *piecewise deterministic and Markovian customer arrival process*, the distribution of which is regarded as known, homogeneous and independent of price. It introduces estimated key parameters of the distribution by observing demand as it arrives. This way, demand can be very precisely described within the limitation of the underlying assumptions.

A concept that focuses more on demand than on its implications is presented by Stefanescu et al. (2004). The fact that correlations between quantities of demand for different products at the same point of time as well as correlations in demand for the same products at different points of time throughout the booking period are considered may be regarded as the major contribution of this work. A *linear mixed effects model* considers both a time component over the time of booking, weighting matrices for correlations of influences by external shocks and a normally distributed error term. Data are unconstrained using the expectation maximisation algorithm. In order to estimate, the parameters of the demand distribution, *maximum likelihood* is applied. However, the use of the results of this approach in optimisation still represents an open challenge.

3 Demand volume

With demand arrival forecasts predicting the rate at which requests arrive over the booking horizon, the question of how much overall demand to expect for a given flight remains open. Demand volume can fluctuate over time due to economic trends, the influence of seasons, trade fairs and holidays, within weekly or daily patterns. As described in Talluri and van Ryzin (2004b) and Armstrong (2001), a variety of statistical methods can be employed in order to pick up these trends and patterns. Two views stand out in this regard: demand may be predicted by considering the data patterns and emulating them with *ad hoc methods* or it may be predicted by considering possible causal relationships between the booking data and influence factors. The later approach is also called *associative*.

Most up-to-date revenue management research seems to focus on demand behaviour as summarised in Section 4 rather than on overall demand development. Research considering the macrolevel of airline demand as it is important for airline fleeting, strategy and general economics goes into the opposite direction. Some examples can be found in Andersson (2001), Abed et al. (2001), Battersby (2005) and Cunningham and De Haan (2006). In any case, some recent considerations of forecasting demand development with regard to airline revenue management are available and summarised below.

In Grosche et al. (2007), the view taken on demand estimation is rather a macroeconomic one, thereby making it difficult to implement in a revenue management system. Still, the authors do offer the opportunity of using their estimates for the optimisation of origin–destination pairs that no historical data exists for yet. In order to calculate the exact connection between *service-related* and *geo-economic* driving forces and demand, two gravity models are implemented. These assume the influencing factors to be independent.

Even if demand is considered stationary, some fluctuation is likely to occur from one flight to the next. Although, generally focusing on spill estimation in the course of fleet assignment, Swan (2002) indicates that a *gamma distribution* of average stationary demand makes sense for revenue management. However, the limitation of this approach is the fact that demand is not in fact stationary.

An appraisal of the influence of prices on customer demand has been documented in Castelli et al. (2003). In contrast to those papers that are listed in Section 4.1, no explicit choice behaviour is assumed here. With an ordinary least squares regression as well as a *multilevel analysis-based methodology*, the variance of price elasticity on different routes in a network has been analysed. With its focus on overall demand as well as on specific routes for specific airlines, this paper straddles the border of macro- and microeconomics: While not offering a straight-forward approach to integrating the findings in revenue management, it provides an opportunity of considering price sensitivity as a determining factor of demand volume.

In order to predict demand over the more up-to-date network view of origins and destinations, Neuling et al. (2004) proposes an analysis of *passenger name records* (PNRs). This data includes information on each passenger's itinerary, including all booked segments. A *no-show forecast* is offered in addition to a regular demand forecast. While the consideration of PNRs presents a novel opportunity of data analysis, it is connected to a significant effort in data mining. Accordingly, the authors underline the challenges of selecting the correct attributes that the forecast then can be based on.

A theory of time series that are influenced by a variety of factors is laid out in Armstrong et al. (2004). The authors describe a concept of decomposing the series in order to represent the causal forces that have an impact on it. However, this method is limited to situations in which it is possible to obtain accurate forecasts for the components of the series that are influenced by the separate factors.

Time series and their reaction to external factors are also the focus of hybrid methods that combine traditional statistics and *neural networks*. An example of such an effort is presented in Aburto and Weber (2007), which combines neural networks with an *ARIMA model*. However, the application described does not consider airlines but instead supermarkets. Furthermore, while it offers the opportunity of predicting demand without formally defining the influence of factors, this lack of formal definition also poses a possible limitation to the concept.

4 Demand behaviour

While the last sections as well as traditional approaches consider the overall amount of demand to arrive for a certain flight or itinerary and a distinct product (booking class), a recent shift in mentality makes other considerations necessary. As laid out, for example in van Ryzin (2005), customers that are ever more informed and flexible require a shift of focus from products to customers. It used to be feasible to merely ask how many units of one product (for instance, business class tickets) would be requested; now it makes more sense to ask how many business class customers (that might also go for a bargain ticket if it is offered to them) do consider leaving their origin at a certain time for a specific destination.

With this new view of demand comes a consideration of dynamic demand behaviour. Customers arrive and choose between alternatives that are offered by the airline and its competition. It is no longer the absolute number of customers that revenue management needs to consider, but also their *choices* with regard to prices, competition and other utilities such as schedule time and transfers. As already indicated in Belobaba (1987), with such choice behaviour, it is possible to recapture rejected customer requests for one booking class on one flight *vertically* (to a different booking class) or *horizontally* (to a different flight).

Different views are taken on demand behaviour. Full knowledge of a customer's way of choosing between alternatives implies a state contingent: depending on the situation, a customer may take a variety of decisions. However, most optimisation methods based on knowledge of customer demand mainly consider a customer's maximum willingness to pay, given a first choice of itinerary, and try to exploit as much of this potential as possible. While traditional methods of forecasting tend to assume that the estimation of overall demand already captures the customer's first choices and maximum willingness to pay, methods based on customer choice attempt to model the complete contingent of considered alternatives.

Furthermore, with more means of comparison and observation of fares available on the internet, customers are becoming less *myopic* and more *strategic*. Research concerned with this aspect of demand behaviour will be summarised at the end of this section.

4.1 Reactions to price

With the advent of *low-cost carriers*, unrestricted fare structures have become more common. In Boyd and Kallesen (2004), the implications of this are outlined in greater detail. Discussions of the low-cost carrier business model can be found in Weber and Thiel (2004) and Dunleavy and Westermann (2005). Such fare structures lead to products that differ in nothing but the price of the tickets. Customer segmentation now needs to focus on which price to offer at which point of time.

At the same time, demand can no longer be assumed to be independent: if some of the offered products only differ in price, the same customer might be interested in any that falls within his acceptable price range. Forecasts and revenue optimisation that are still based on a concept of independent demand will therefore lead to a *spiral down effect* as outlined in Cooper et al. (2006). More and more demand is predicted for the booking class with the lowest price, and accordingly, more and more capacity is reserved for this class.

Another connected problem that arises is *buy-down*, the possibility that customers with a high willingness to pay are offered a low price and accept it. Simulation results with regard to the performance of traditional revenue management under these issues are offered in Cusano (2003) and Ozdaryal and Saranathan (2004).

The challenge of revenue management under these conditions becomes to include information on customer price elasticity in the forecasting models. As will be listed in the following paragraphs, different approaches formulate this under different concepts such as *maximum willingness to pay, utility functions, customer demand curves, sell-up-rates and frat-5*.

In Talluri and van Ryzin (2004a), a customer choice model as described in Section 4.3 is implemented in order to estimate the connection between prices and customer demand. The customers' *utility function* in this case is limited to the fares that are offered and does not consider other factors. After the model parameters are estimated using maximum likelihood methods, this paper offers optimal policies for an independent view of demand, a *multinomial logit model* and a model in which customers always purchase the lowest available fare.

Some approaches to forecasting demand under the assumption that customers cannot be segmented by restrictions are presented in Cléaz-Savoyen (2005). The findings are accompanied by simulation results as attained through the Passenger Origin–Destination Simulator developed by Hopperstad at the Boeing Company (see also Gorin, 2000; Hopperstad, 2000; Reyes, 2006; for introductions). Building up on research documented in Bohutinsky (1990), Belobaba and Weatherford (1996) and Gorin (2000), the thesis concentrates on combinations of *Q-forecasting* and *fare modifiers*.

Q-forecasting models the behaviour of customers by calculating the amount of passengers that will be willing to buy the class with the lowest fare – *Q*. Subsequently, the amount of passengers willing to buy up to the next higher priced class is predicted from estimates of sell up rates. These estimates are formulated as *Frat5-rates*: the price-ratio of two classes at which 50% of the demand for the lower priced class will be willing to buy up to the higher-priced class. Frat5-rates are estimated dynamically over the booking horizon via a regression across time frames.

Building up on Cléaz-Savoyen (2005), Reyes (2006) offers forecasting methods for a combination of restricted and unrestricted fare-classes referred to as *hybrid fare structures*. He describes the challenge in such an environment as the separation of *price* and *product-oriented* demand. A similar statement can be found in Boyd and Kallesen (2004), where the two demand segments are called *priceable* and *yieldable*. While a product oriented customer is primarily interested in purchasing a certain product (a ticket with or without specific restrictions) with less regard to the price, a price oriented customer will be looking to buy at the lowest available price with little regard to the restrictions.

Two understandings of *hybrid forecasting* are introduced in Reyes (2006): the simultaneous deployment of two separate forecasting methods for the two customer segments or the separate forecasting of two fare-structures; restricted and unrestricted. The concept itself is ascribed to Belobaba and Hopperstad (2004). Combined with it are two more methods: fare adjustment as outlined in Fiig and Isler (2004) and *path categorisation*. The later assumes that willingness to pay is related to the amount of transfers a passenger's way over an O&D network includes. Tests conducted with the help of the Passenger Origin–Destination Simulator are cited to show that both fare adjustment and path categorisation can significantly improve network revenue if hybrid forecasting is applied.

Finally, fare modifiers as a concept developed in Fiig and Isler (2004) are introduced to optimise revenue for flights that have both a restricted and an unrestricted fare structure, thereby catering both to price sensitive customers and to those predicted the traditional way. Fare modifiers also rely on sell up estimates; however, they do not necessarily assume that all lower priced classes are closed (as this is unnecessary in a restricted fare environment).

The common limitation of all of the aforementioned works is their reliance on the passenger O&D simulator (PODS) model of demand as well as on the assumption that sell up rates are known and can be further processed. The concepts developed in this way do, however, offer opportunities towards the immediate implementation of the methods described in applied revenue management.

4.2 Reactions to competition

After the consideration of a product's price having an influence on customer demand, the next step is to consider the influence that prices for comparable products offered by the competition have. While it seems obvious that low competition prices lead to lower demand for airlines that offer higher prices, the exact relationship needs scientific focus.

In Fischer and Kamerschen (2003), an analysis of demand aggregated to airport-pairs and its connection to the market situation in terms of competition is presented. The authors employed the *Rosse-Panzar test* in order to measure the consequences of competition on airline markets. However, the conclusions of this examination are not so much revenue management recommendations as they are general statements about economic implications: The more intense competition gets, the lower the average air fare tends to be. It is stated that with regard to the data used, airline competition is not as perfect as often supposed.

An approach that focuses more on *game theory aspects* of airline revenue management under competition is documented in Netessine and Shumsky (2005). Considered are both *vertical* (different airlines compete on different legs of a multileg itinerary) and *horizontal* (different airlines compete on the same leg) competition. Conditions for *Nash equilibrium* are provided as desired characteristics of the demand distribution. However, no method of estimating the real consequences on a given population is provided.

A game theoretical view of revenue management is also taken in Gallego et al. (2006). Revenue management under competition is regarded as a *sequential* and as a *repeated* game, however, with no special regard to the airline industry. Again, conditions for a Nash equilibrium are outlined and the advantages of competitors cooperating are pointed out. That condition, however, is very difficult to realise under the legal circumstances of airline revenue management.

Another example of the inclusion of such information in revenue management is provided by Walczak (2005). However, while knowledge of the influence of competition offers on demand is included in a dynamic programme according to this presentation, this knowledge is regarded as given. Its estimation is not part of the research.

In Coldren and Koppelman (2005), the volume of demand for airline travel along itinerary shares of competing airlines is predicted. The model offers the opportunity of calculating the influence of departure day, brand and service. Both a multinomial logit model and variations of the nested model are considered in order to analyse the influence of these factors. The price differences between the different airlines' offers are not considered, which imposes a limitation on the model from a revenue management point of view.

In the course of research conducted with the PODS, some concepts for including knowledge of competitor offers in the estimation of sell up rates have been outlined. These, and the resulting, findings have been presented at several PODS summits. Recent examples can be found in Guo (2007), Hopperstad (2007) and Carrier (2003). In addition, research concerned with fare adjustment as described in the previous section underlines that the consideration of customer reactions to prices becomes even more important in markets with intense competition (Kayser, 2007). Finally, with matching the lowest competitor price, an approach to revenue management with regard to the competition that avoids actually forecasting the customer reaction is presented in Lua (2007a–c). While these publications provide novel insights to the consequences of competitive strategies in revenue management, they are of limited practical value in so far that knowledge on competitor prices is regarded as given.

It can be concluded that much research that exclusively considers the effects of competition does so with regard to general consequences for revenue management. Forecasting methods that do consider a wider range of influence factors often offer the possibility of including competition prices or simply the existence of competition in the model. A summary of recent developments in such methods can be found in the next section.

However, in Gallego and Hu (2007), demand models that do consider more characteristics of the product as decision factors for customers are examined with special regard to competition. *Dynamic pricing* is presented as the way of building up on demand forecasts that do incorporate such a customer model. With consideration of the single-leg model, the authors extend both on Netessine and Shumsky (2005) and Gallego et al. (2006). With regard to the airline industry, cooperation is excluded. An *open-loop Nash equilibrium* is presented, however, changes in customer demand as caused by competition are ascribed to the predictions of a customer choice model. Such models, which can include the ticket price, competition offers, and further utilities of the products offered, are described in the next section.

A simulation framework in which competition strategies may be evaluated is presented in Abdelghany and Abdelghany (unpublished). However, while methods for calculating the results of different ticket distribution strategies in a competitive market are presented, no forecast methods including knowledge of competition are explicitly outlined.

4.3 Other utilities

While the exclusive consideration of prices for customer decisions is gaining in importance with the rise of low-cost carriers, other factors contribute to customer choice behaviour. It is intuitively appealing that when buying tickets for trips across a network, customers should consider the travel time as well as the amount of transfers and time spent in between flights. An example of the examination of travel choices and risk taking can be found in Theis et al. (2006). Furthermore, though focusing on the mix of unrestricted and restricted fare structures and therefore listed in Section 4.1, Reyes (2006) mentions a connection between willingness to pay and transfers. This paper includes this connection by applying path categorisation. Further methods of incorporating utilities other than price and competition prices are listed in this section.

The idea that customer choice can be dependent on the distribution channel or characteristics of the travel itinerary is outlined in Walczak and Brumelle (2007). This paper includes the idea that whether or not a customer buys a ticket depends on the price but assumes that the customer's demand function with regard to the price is known to the airline. Arrival rates derived from the demand function are included in a Poisson process, the use of which in literature has been described in Section 2. Anyhow, now *customer profiles* are included in the arrival process, thereby making customers' demand functions variable with regard to different offers. Comprised in these is also the so-called *market state*, the competitive situation. The paper refers to Walczak (2005) at this point, a presentation that is recounted in Section 4.2.

The exact quantification of the influence that characteristics of the offered product and the market state have on customer demand curves is relegated to *consumer choice behaviour models*. Among these, *discrete choice models*, when customers do have to choose exactly one of several distinct alternatives, have special interest for revenue management. The theory of discrete choice models with special regard to revenue management and parameter estimation via maximum likelihood has been described extensively for the first time in Ben-Akiva and Lerman (1985). On this theoretical background, a multitude of research has evolved.

In Talluri and van Ryzin (preprint), a *multinomial logit model* of demand is developed in order to predict customer choice. This regression model for utility functions implements logistic regression for more than two variables. The probability of a customer buying a product is calculated as a natural logarithm defined by a linear function. The model parameters (arrival rates as well as choice factors) are estimated via expectation maximisation. Given this model, revenue is optimised for the single-leg multiple-fare case with the help of a dynamic programme. The complexity of such programmes increases over the available seats as well as over the number of itineraries and fare-classes – this issue is also referred to as the *curse of dimensionality* (see e.g. Bertsimas and de Boer (2005) for a description as well as an attempt of solution). Therefore, most research considering customer choice models and dynamic programmes only consider one leg at a time, limiting its applicability to real-world problems. A similar model is also applied in Talluri and van Ryzin (2004a), however, only the prices that are offered at the time the customer makes his choice are considered.

An examination of price sensitivity with special regard to customers that buy airline tickets online is documented in Garrow et al. (2007). The authors used *stated preference* data in order to estimate a multinomial nested logit model of customer choice behaviour. As a consequence of the decision of using stated preference data, this paper draws special attention to matters of survey design and recruitment. Both ticket prices and socio-demographic factors are included in the analysis. The attempt is made to explain willingness to pay through other utilities. This approach seems to have weaknesses only in so far as that stated preference data is of limited reliability.

Finally, a new way of applying choice-based revenue management is provided in Vulcano (2006). *Simulation-based optimisation* is offered as a way of building up on forecasts that incorporate this model. Apart from the already mentioned multinomial logit model of choice, alternatives such as *finite-mixture logit*, *Markovian second choice* and *general random utility* are mentioned. The author also distinguishes between the estimation of choice parameters and that of volume parameters. In this paper, forecasting methods for the later have been presented in Section 3. In order to estimate choice parameters, both expectation maximisation and maximum likelihood are proposed. The estimated demand behaviour is used as a demand stream input to the simulation used to optimise the seat allocation. This method gives the opportunity for both considering arbitrary dependencies between the classes and flights as well as exact optimisation. It appears to be limited only with regard to the detruncation employed. Methods for demand detruncation are summarised in Section 5.

4.4 Strategic behaviour

Especially with the rise of dynamic pricing, customer behaviour over the course of longer amounts of time has gained in importance. The underlying idea is that customers might behave *strategically*, using their experience in order to book at the point of time when their expectations for low fares are highest. Research that has been conducted in this regard is mostly connected to game theory and pricing and only includes little advice towards the estimation of customer behaviour. Nevertheless, in order to give a conclusive overview of demand forecasting, some recent developments are included here.

An introduction to the concept of strategic customers is given in Anderson and Wilson (2003). This paper states that with the new availability of information on the internet, it is possible for customers to monitor historical booking and price information just as the airlines do for their revenue management systems. Thereby, they might gain an understanding of the airline's pricing strategy and purposefully undermine it. While no means of estimation are offered, the negative implications of continuing to use traditional optimisation strategies when confronted with strategic customers are outlined.

A general concept of recognising and dealing with returning customers is documented in Fudenberg and Villas-Boas (2006). This is referred to as behaviour-based price discrimination. While the phenomenon is introduced at length, no applicable methods for airlines are offered. However, an additional excursion on consumer privacy and the possible consequences of strategic consumers trying to avoid having their utility functions known is interesting with regard to consumer choice models.

In Xu and Hopp (2005b), the consequences of strategic customers for revenue management are once more laid out with special regard to dynamic pricing. In this case, however, strategic behaviour mostly refers to the change of price sensitivity over the course of time. As this is connected to customer expectations, price sensitivity tends to rise for customers of the retail industry while it is lowered as the date of departure for a flight comes nearer. Another study of the impact of strategic customer behaviour is documented in Zhou et al. (2006).

More thought has been devoted to revenue management in the presence of strategic customers. Examples can be found in Levin et al. (2005, 2006), Wilson et al. (2006) and Su (2007). However, little can be found on the prediction of this strategic behaviour or the estimation of its intensity.

5 Demand detruncation

Detruncation or *unconstraining* describes the idea that booking data as it is stored by the airlines does not represent the actual demand. Customer requests are constrained by the amount of tickets that the airline offers. Without further information, it is unknown whether more tickets could have been sold, unless offer exceeded demand. A general introduction to this topic is also presented in Pölt (2000).

In Zeni (2001a), which is also cited in Talluri and van Ryzin (2004b), the author extensively presents and compares a number of unconstraining methods. His findings are also summarised in Zeni (2001b). Among the listed concepts are ignoring the censoring, discarding the censored data, *mean imputation method*, the *booking profile method*, *expectation maximisation* and *projection detruncation*. While weighting the methods against each other and finding estimation maximisation to be superior, the study does not introduce new concepts.

To ignore the censoring or to discard the censored data are the easiest alternatives. The mean imputation method, a variation of *pickup* unconstraining and the booking profile method are both ways of estimating unconstrained values by extrapolating from the mean of bookings that were not truncated. Expectation maximisation uses a normal distribution and maximum likelihood in order to iteratively estimate the parameters influencing demand. Finally, projection detruncation is a variation of expectation maximisation that uses a parameter τ in order to scale the amount of unconstraining applied to the data.

In the conclusion of Zeni (2001b), the author judges that anything is better than to ignore the truncation, however, while intricate and computationally intense, expectation maximisation works best. Such findings are also confirmed by Weatherford (2000) and Weatherford and Pölt (2002).

While claiming not to use any forecasting techniques, van Ryzin and McGill (2000) solves the problem of unconstraining data by applying *life tables*. This method is taken from *survival analysis* and is implemented to estimate parameters of a survival function. It indicates how many more requests might have arrived after a booking class was closed. Tests indicate mixed performance, therefore, its implementation is only recommended for small or start-up airlines or in situations with demand that is difficult to predict.

A new method of unconstraining is proposed in Ferguson et al. (2007). It makes use of *double exponential smoothing*, also called '*Holt's Method*'. As with many other mathematical solutions to forecasting problems, this method is outlined in greater detail in Armstrong (2001). Two smoothing constants are introduced in order to calculate both the base demand and the trend. An application is described both for the case of monotonously closing booking classes and for the case of booking classes being reopened. Based on simulated customer requests, the new method is compared to an averaging method, expectation maximisation and projection detruncation as taken from Weatherford and Pölt (2002), as well as the method of life tables described in van Ryzin and McGill (2000).

The results are generally favourable but do vary with regard to the simulated customer behaviour. Lan and Gao (2007) offer another approach to dealing with limited demand information. The authors developed robust methods of controlling bookings when only upper and lower boundaries for demand are known. The concept is shown to be effective; however, it is limited to single-leg problems. The fact that most up-to-date revenue optimisation is computed on a network level makes this method as well as its preceding research on *competitive online algorithms* in Ball and Queyranne (2006) hard to apply.

While other industries profit from available *turn-down data* (see for instance Zhu, 2006), such data are not available for airlines. Turn-down data stores customer requests that have been denied in addition to those that were turned into bookings. If this data were available, no unconstraining would be necessary.

The nearest comparable information is that of so-called *click-streams*. These records of customer behaviour as observed on travel websites give an optimistic view of their possible buying decisions. However, they are biased on the side of over-estimation, as the customer does not seriously consider all travel-itineraries that he looks at. The possible importance of this kind of data for future revenue management forecasting is hinted at in Nason (2007). However, no published research on working with this kind of information in the airline business could be found by the author.

6 Conclusions

As can be seen from this overview, much development has taken place in demand forecasting for airline revenue management even in the last 10 years. Especially, with regard to a shift from product focus to customer focus and a strong trend towards less restricted products, this kind of forecasting has gained significance.

However, as a multitude of methods is offered, very little has been done about systematic comparisons so far. While most papers that introduce new methods also give examples of comparisons, those have been picked by the authors themselves. It seems difficult to find the 'right' forecasting method for a given situation.

At the same time, comparing the outcomes of forecasts that do tend to influence their own outcome is difficult. As described in Section 5, booking limits that are based on forecasts lead to biased historical booking data.

Only a simulation system in which customers are generated in the manner of the Passenger Origin–Destination Simulator might be able to consider the complete process. Concepts for the evaluation of seat allocation strategies have already been described in Abdelghany and Abdelghany (2007) and Frank et al. (2008). If all other modules (customers, optimisation and allocation) can be kept the same, the forecast and simulated customer demand can be compared. The development of such a system is the task of further research.

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