Practice Article

The history of forecasting models in revenue management

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ABSTRACT Forecasting has been used in revenue management (RM) for nearly the last 60 years. This brief, historical article surveys over 80 articles from the recent period and traces the evolution of RM forecasting models. The natural breakdown of forecasting sub-categories that are covered within the airline industry include: origin–destination forecasting and whether to aggregate or disaggregate the data, user adjustment, hybrid forecasting in less-restricted fare environments, seasonality, forecast accuracy and choice-based forecasting. We also review RM forecasting in the hotel and other industries.

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INTRODUCTION

Since the early days of the practice of revenue management (RM), no one can doubt the importance of the forecasting engine that provides the input of unconstrained demand to the more mathematically sophisticated optimization engine or that provides the input of the no-show rate forecast to the overbooking engine. Indeed, forecasting is an important part of any business. In this article, we will look back at the history of forecasting in the RM context (58 years).

HISTORY AND LITERATURE REVIEW ON FORECASTING

In all RM situations, the forecast is the critical input that determines the booking limits, which in turn, largely determine the airline profitability from each and every flight. Forecasting includes both projections of demand by booking class, as well as the no-show rate by flight (or booking class). This latter forecast is fed into the overbooking engine in order to determine the optimal overbooking level, but we will not consider overbooking itself in this article.

Table 1: Forecasting research (1958–2016)

Beckmann and Bobkoski (1958)	McGill and van Ryzin (1999)	Kambour (2006)
Taylor (1962)	Viswanathan (1999)	Chen and Kachani (2007)
Lyle (1970)	Westerhoff (1999)	Chiang *et al* (2007)
Littlewood (1972) (re-published in 2005)	Kalka and Weber (2000)	Fiig (2007)
Taneja (1978)	Loew (2000)	Mukhopadhyay *et al* (2007)
Harris and Marucci (1983)	Salch (2000)	Muzich and McLellan (2007)
Yesawich (1984)	van Ryzin and McGill (2000)	Zeni (2007)
L' Heureux (1986)	Zaki (2000)	Kambour (2008)
Adams and Vodicka (1987)	Campbell and Williams (2001)	Ball and Queyranne (2009)
Ben-Akiva (1987)	Weatherford *et al* (2001)	Cleophas *et al* (2009)
Sa (1987)	Zaki (2001)	Fiig *et al* (2010)
Lee (1988, 1990)	Zeni (2001)	Ozdaryal (2010)
Kimes (1989)	Pölt (2002)	Vulcano *et al* (2010)
		Haensel and Koole (2011)
Weatherford (1991)	Menich (2003)	Sun *et al* (2011)
Smith *et al* (1992)	Weatherford *et al* (2003)	Fiig *et al* (2012)
Wood (1992)	Weatherford and Kimes (2003)	Gorin (2012)
Weatherford *et al* (1993)	Westerhoff (2003)	Jain (2012)
Hopperstad (1994)	Zeni (2003)	Kambour (2013)
Nahmias (1994)	Belobaba and Hopperstad (2004)	Lemke *et al* (2013)
McGill (1995)	Boyd and Kallesen (2004)	Oancea and Bala (2013)
Wickham (1995)	Garrow and Koppelman (2004)	Weatherford (2013)
Botimer (1997)	Neuling *et al* (2004)	Carrier and Weatherford (2014)
Pölt (1998)	Salch *et al* (2004)	Fiig *et al* (2014)
Bach (1999)	Schwartz and Cohen (2004)	Weatherford (2014)
Chatterjee and Summerbell (1999)	Baker and Murthy (2005)	Dutta and Marodia (2015)
Isler and Morel (1999)	Stefanescu (2005)	Weatherford (2015)
	Gorin *et al* (2006)	Carrier and Weatherford (2015)

This broad overview of the literature provides a review over a 58-year period (1958–2016) of research on forecasting as used in RM. The overview includes a bibliography of 83 articles on forecasting. The forecasting articles have been summarized in Table 1 by year of publication. We make no claim to successfully identifying all RM forecasting publications and certainly regret any that we might have missed. We further note the existence of a companion article on *unconstraining* that was written for this same special issue of *Journal of Revenue and Pricing Management* (Weatherford, forthcoming).

The sections below are organized by industries (airline, hotel, other) as well as some subheadings within the airline industry (origin–destination [O–D] forecasting/aggregation versus disaggregation, user adjustment, no-show forecasting, hybrid forecasting [HF] in less-restricted fare environments, seasonality, forecast accuracy and choice-based forecasting).

Airline industry

The airline industry was the first to use forecasting in an RM setting. Some of the factors that make forecasting in the airline environment so challenging include: seasonality, including time-of-day, day-of-week and week-of-year variability; demand dependencies between booking classes; sensitivity to pricing actions in a hypercompetitive industry; demand volatility; schedule changes; truncation of historical demand data; reservation system limitations; and an industry that is highly susceptible to external shocks like wars, viruses, fuel prices and so on. On top of all this volatility at the leg/class/departure-date level, airlines also have massive volume – they typically track flights at least 330 days out, with up to 26 different booking classes – multiplying this by 5000 flights per day means 42.9 million forecasts are being generated at any one time.

The earliest description of forecasting models for passenger bookings and cancellations are found in Beckmann and Bobkoski (1958) and Taylor (1962). As their main focus was on no-shows, we will cover them in more detail in the no-show forecasting subsection below. About a decade later, Lyle (1970) modeled demand as composed of a γ distribution with Poisson random errors, which gives a negative binomial distribution for total demand. Littlewood (1972) used data from British Airways to forecast final load factors based on advanced bookings from 1 to 13 weeks in advance. He was the first to propose aggregating flights from low-demand O–Ds into broader categories (for example, Europe to Nairobi). Traditional regression techniques for aggregate airline forecasting are described by Taneja (1978).

In the 1980s and 1990s, most researchers felt that some of the best information on potential future bookings was contained in the current bookings for the same (or similar) flights in earlier weeks. The use of such short-term booking information has been discussed by many airline practitioners, such as: Harris and Marucci (1983) at Alitalia, L'Heureux (1986) at Canadian Airlines, Adams and Vodicka (1987) at Qantas and Smith *et al* (1992) at American Airlines. Typical applications use simple exponential smoothing (ES) techniques to incorporate partial booking data from related flights at different phases in their booking process. The doctoral dissertation of Lee (1990), and his earlier work (Lee, 1988), discussed many issues in disaggregate airline demand forecasting and incorporated censoring in estimation of Poisson models for the booking arrival process. Weatherford (1991) and Weatherford *et al* (1993) incorporated diversion (or upsell) in a stochastic model of booking arrivals for two classes. Wood (1992) looked at the forecasting of group demand. Wickham (1995) looked at time series, linear regression (LR) and two kinds of pickup (PU) models. He found that the advanced PU model outperformed the rest and that 7 weeks of historical data was best. Botimer (1997) discussed the effects of promotional sales on forecasting. Pölt (1998) estimated that a 20 per cent reduction of forecast error could translate into 1 per cent incremental revenue generated from the RM system, thus emphasizing the bottom-line importance of pursuing better forecasting methods. Viswanathan (1999) reviewed various additional forecasting methods (including neural networks, principal component analysis and adaptive models) as well as a proprietary Sabre model (not tested on any airline data) and concluded that the future would involve research on passenger choice models, wavelets, multivariate regression splines and variations on neural networks. McGill and van Ryzin (1999) provided an excellent research overview on the entire RM research area, including forecasting, but also unconstraining, overbooking, leg seat inventory control, network optimization and pricing.

Forecasting is difficult, costly and the results are sometimes unsatisfactory. Therefore, some researchers have tried to find alternative approaches. Moving into the 2000s, van Ryzin and McGill (2000) presented a simple adaptive approach to optimize seat protection levels in airline RM. Instead of using the traditional approach that combines a forecasting method with a seat allocation heuristic, their approach used historical observations of the relative frequencies of certain seat-filling events to guide direct adjustments of the seat protection levels. A preliminary study suggested that the method could augment traditional forecasting/optimization, though no one has implemented this idea. Zaki (2000) gave a summary of forecasting and stated that as new business models keep emerging, old forecasting methods that worked well before may not work very well in the future. Weatherford *et al* (2003) examined neural network forecasting to see if it could outperform previously studied forecast methods and found that it performed slightly better than ES, LR and moving average (MA) models as measured by mean absolute percentage error (MAPE) on a holdout sample. Baker and Murthy (2005) found that when looking at the potential of using auctions as a new price distribution channel, counterbalancing forecast errors was very important and determined that it was critically important not to err on the side of overestimating market willingness to pay. Zeni (2007) challenged the validity of using historical data given the proliferation of less-restricted fare products in the airline industry and encouraged airlines to focus on developing customer choice models, rather than relying on traditional forecasting methods. Ball and Queyranne (2009) looked at the RM problem from the perspective of finding online algorithms that could eliminate the need for demand forecasts.

O–D forecasting and aggregation versus disaggregation

There are thousands of potential itineraries across a hub-and-spoke airline network. Some itineraries between major centers are traversed frequently enough that reasonable estimates of demand for those itineraries can be obtained. Many others are rarely traveled; thus, demand based on historical data is near zero. Unfortunately, taken together, rare itineraries form an important revenue component. Around the turn of the century, many people started researching O–D forecasting. Isler and Morel (1999) and Chatterjee and Summerbell (1999) were the first to address it at Agifors meetings. The former discussed Swissair's experience, while the latter discussed different hierarchies to use in creating O–D forecasts. They warned of hidden correlations in the data at different levels of aggregation. Salch (2000) addressed the importance of finding the right hierarchy of clustering to make the O–D forecasts meaningful. He showed results that beat leg forecasting by a small amount (0.05–0.15 per cent). Next followed Campbell and Williams (2001), who discussed aggregation of scale-free statistics for small O–D markets. Their research suggested that it is unlikely that any method could be devised to predict the probability of individual, rare O–D itineraries. The only recourse is to aggregate such itineraries into larger groups and average their fare values. Aggregating data in order to get greater stability in the forecast numbers, always leaves the challenge of how to split it back out to the O–D/fare class (ODF) level needed if using O–D optimization and whether that splitting process introduces more error than just forecasting at the ODF level in the first place.

Pölt (2002) chronicled Lufthansa's multi-year experience in building an O–D forecaster. They found a 20:90 rule where 20 per cent of the O–Ds accounted for 90 per cent of the traffic and were pleased with their forecaster's performance. Westerhoff (2003) discussed KLM's implementation of an O–D forecaster and also the various aggregation approaches used to solve the 'small numbers' problem. Fiig (2007) presented SAS's journey with developing an O–D forecasting system and seven different levels of aggregation used. Gorin (2012) described different ways PROS used clustering to segment data into different hierarchical schemes. Lastly, Oancea and Bala (2013) described their experience at Qatar Airways when forecasting at an even more detailed level – the O–D/itinerary/point of sale/fare class/departure date level.

User adjustment

Despite the many numerical forecasting methods that have been developed, it turns out that human judgment is still indispensable in forecasting airline demand. Bach (1999) was the first to report an experiment at Northwest Airlines where they put a small subset of markets on autopilot (no user intervention) in a single month of the fall of 1995 and compared the performance with the same markets 1 year earlier and found that analysts added 7.9 per cent revenue improvement and adjusted more than 50 per cent of the bucket-level forecasts. Loew (2000) discussed a successful study at America West to help analysts focus on the main part of the overall RM process where they could add the most value – to correct flights with strong negative bias. Zeni (2003) presented a study at US Airways (all flights, single day) where they found that analysts added up to 3 per cent incremental revenue. Schwartz and Cohen (2004) did a study on 57 experienced RM analysts to evaluate the bias of human subjective judgment. They found that the nature of the user interface influenced the way the analysts adjusted the forecasts. Mukhopadhyay *et al* (2007) found that user intervention was most helpful for the major airline studied when competitor airlines were adding flights to a given market. Finally, in looking at forecast multipliers (FMs) used by RM analysts, Weatherford (2015) found that an FM of 1.1 or 1.2 could maximize revenues by providing revenue lift of 0.5–1 per cent in a large global network of 572 O–D markets with four competitors.

No-show forecasting

The earliest description of forecasting models for no-show behavior was found in Beckmann and Bobkoski (1958). They tested three different distributions (γ, Negative Binomial and Poisson) for total passenger arrivals and showed that the γ distribution provided the most reasonable fit. In 1962, Taylor calculated probability-generating functions for booking behaviors that determined show-ups. He made allowance for cancellations and no-shows. The generating function was used to estimate parameters of a distribution for forecasting final show-ups.

Kalka and Weber (2000) were the first to use the passenger name record (PNR) as a data source to improve accuracy of no-show forecasting. They used rule generation through induction trees on Lufthansa data and found that they could reduce the no-show rate error from 12.4 per cent to 9.5 per cent. Neuling *et al* (2004) also used PNR data to improve no-show forecasting accuracy. They found an overall improvement of 1–2 per cent in forecast accuracy. Garrow and Koppelman (2004) used multinomial logit models and found that passengers who have not paid and do not have an e-ticket are 86 per cent more likely to no-show on outbound flights. Gorin *et al* (2006) looked at a blended cost-based, PNR-adjusted approach to no-show forecasting and found a revenue gain of up to 10 per cent per available seat mile compared with using historical average no-show rates. Kambour (2006) analyzed 6 months of departure data (over 500K PNRs) using ANCOVA and found a 2.1 per cent improvement in the mean squared error using a PNR-based no-show model. Further, he found that the following factors were significant: point of sale, leg origin and destination, departure time, class of service and day-of-week. With this grouped PNR model, error was improved by 4.8 per cent. Lemke *et al* (2013) analyzed data from Lufthansa Systems (LS) and attempted to increase *net* booking forecast accuracy by modifying the cancellation forecast. By looking at combined forecasts, they were able to improve forecast accuracy by 7.3 per cent over a basic LS forecast.

HF in less-restricted fare environments

In order to deal with the rapidly changing fare-restriction environment of the mid-2000s and forward, some airlines have added new modules that perform either HF if the network has a mix of unrestricted and more restricted markets (Boyd and Kallesen, 2004) or Q-forecasting (Belobaba and Hopperstad, 2004) for networks with fully unrestricted markets. The latter authors presented the concept that in markets with few or no restrictions, all of the demand will eventually spiral down to the bottom fare class (Q). HF has become the industry standard for handling semi-restricted/un-restricted fare structures and has been successful at reducing 'spiral down'.

Cleophas *et al* (2009) described an approach to evaluate the quality of demand forecasts in a spiral-down environment using a simulated framework. The seminal piece on HF and fare adjustment (FA) is Fiig *et al* (2010), where the FA transformation is described that changes the fares and demand of a general, discrete choice model to an equivalent, independent demand model. This allows the continued use of the regular optimization algorithms of traditional RM systems. Further, Fiig *et al* (2012) applied these FAs to 'fare families' – an innovative approach to pricing and branded fares that was pioneered by Air New Zealand, Air Canada and Qantas. Kambour (2013) developed a willingness-to-pay distribution from actual paid fares data and indicated that his model worked best for fare families. Weatherford (2013) explored the parameter settings for HF in a domestic network with two competing airlines that could maximize revenue in a less-restricted fare environment and concluded that moderate estimates of willingness to pay were generally best and could improve revenue 2–6 per cent in less-restricted environments and 3–16 per cent in fully unrestricted environments. He then extended the study (Weatherford, 2014) to look at a larger global network with four competing airlines and found that under network optimization, by getting more aggressive with HF and FA, revenue can be increased by 0.5–2.0 per cent. Fiig *et al* (2014) explored better ways to measure forecast accuracy in an environment with less-restricted fare structures by introducing a constrained forecast accuracy measure and provided PODS simulation results that supported their new approach.

Seasonality

Sa (1987) concluded that the use of regression techniques using day-of-week dummy variables and bookings-in-hand can improve the performance of RM systems when compared with Box-Jenkins ARIMA models (too hard to tune) or simple historical MAs. Westerhoff (1999) looked for seasons in KLM demand data that was aggregated at different levels. He found that using a flexible start and end date to a season improved forecast quality by 2–5 per cent as measured by mean absolute deviation over their prior two-season model. Muzich and McLellan (2007) examined seasonality with US Airways data at the most disaggregated level (3800 daily flights) and found a 9 per cent reduction in error (MAPE) compared with their prior approach. Jain (2012) studied seasonality at United and used business knowledge to define meaningful clusters of data.

Forecast accuracy

Loew (2000) did a 'forecast versus actual' analysis on America West data and found that they could significantly reduce bias 60 days before a departure by training their analysts to look for flights on which to intervene more strongly. Salch *et al* (2004) proposed some early steps in using competitive fare data to improve forecast accuracy. Kambour (2008) identified two important factors when measuring accuracy: (i) airlines must compare apples with apples (for example, they should not compare unconstrained forecasts to constrained actuals) and (ii) demand will tend to be constrained more often when it is above the mean, thus throwing out constrained observations will bias the estimate of demand downward. Ozdaryal (2010) discussed two alternatives that United adopted to better quantify forecast accuracy – one simulation based, the other based on 'stress-tested' assumptions about demand.

Choice-based forecasting

There has been significant research activity in many disciplines on discrete choice behavior modeling using multinomial logit estimations.

A basic reference specifically directed at transportation demand modeling is that of Ben-Akiva (1987). Smith *et al* (1992) briefly discussed the potential of discrete choice modeling. Hopperstad (1994) discussed the potential of path preference models for detailed prediction of passenger behavior. A more recent study was Vulcano *et al* (2010), who developed a theoretical choice-based model for estimating demand in unrestricted fare-class markets, and then tested it with data from a major airline in a single O–D market (from New York City to a leisure destination in Florida). Their simulation results showed a 1–5 per cent average revenue improvement using choice-based forecasting. Carrier and Weatherford (2014) have begun looking at estimating a model of airline passenger choice using available booking data and least squares regression and have seen some promising results.

Hotel industry

Yesawich (1984) did an early study on how hotels could look at market demand and then factor in a property's penetration rate, analyze competitive practices and then determine the proportion of marketing effort to be applied to each market segment. Kimes (1989) was the first to apply general RM techniques to the hotel industry. Weatherford *et al* (2001) discussed different ways to forecast demand for hotel RM systems and assessed the effectiveness of using an aggregated forecasting approach versus disaggregated. Next, Weatherford and Kimes (2003) used data from Choice Hotels and Marriott Hotels to compare seven forecasting methods (ES [single & double], MA, LR, logarithmic LR, additive PU, multiplicative PU) for hotels to find the most accurate method. After analyzing 112 data sets, the following forecast methods were chosen (per cent of time indicated in parentheses): single ES (33.3 per cent), additive PU (25.1 per cent), MA (15.4 per cent), double ES (12.9 per cent), LR (10.9 per cent), log LR (2.1 per cent), multiplicative PU (0.3 per cent). Thus, single ES, additive PU and MA models provided the most robust forecasts. Later, Chen and Kachani (2007) analyzed hotel data with five forecasting techniques (single ES, LR, classic PU, additive PU, combination of ES and additive PU) and found that ES with 8 weeks of history performed best on their data. Haensel and Koole (2011) tested their singular-value decomposition approach on three different real hotel data sets using penalized least squares and reported an average improvement in forecast accuracy (MSE) of 15 per cent over Holt-Winters exponential smoothing.

Other industries

Zaki (2001) presented a forecasting method (contingency table with reservations and actuals) that worked in the truck rental market. Chiang *et al* (2007) provided a review of recent developments in RM broadly defined (that is, forecasting as well as other areas) in other industries – cargo/freight, internet service and retailing. Sun *et al* (2011) tested 14 different forecasting methods (ES, MA, double ES, ARIMA; classic PU methods using LR, log LR, MA, ES, ARIMA; and advanced PU methods using same five) using data from a cruise line. They found that classical PU methods and ARIMA models performed best. Dutta and Marodia (2015) looked at various forecasting techniques in the rail industry and found that a weighted, combined forecast (using both time series and regression) could reduce MAPE by 10 per cent on most days of the week.

FINAL THOUGHTS

There are so many forecasting ideas and combinations that can be studied, therefore we believe that this will be a fruitful field of research for years to come. Even though computers are designed to crunch forecast numbers extremely fast, there will always be a need for humans. Manual intervention is required on an exception basis for critical markets and to anticipate the impact of changes in prices, flight schedules or other important aspects of market structure. Much work remains to be done – the potential benefits of sharper forecasts certainly justify substantial investments in forecasting methodology and market analysis. Finally, with the International Air Transport Association working on developing uniform standards by 2016 for airlines to create a new distribution capability, there will be even more opportunity in the future for airlines to customize offers to individual passengers and thus make forecasting even more reliant on models that incorporate customer choice.

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