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Airline Seats Allocation Optimization Through Revenue Management

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ABSTRACT

Revenue Management has recently gained a solid recognition in Airline industry. It acts as a strategic and tactic provider to manage the uncertainty in demand for their perishable products in the most profitable manner as possible. The Airline Revenue Management tries to attain an effective seat inventory control by utilizing the forecasts of future bookings, the revenue values related with each fare class, and the booking requests by the passengers which in turn will maximize the total revenue of a flight. This paper attempts to propose a novel approach in optimizing the seat inventory control by jointly utilizing the statistical forecasting together with revenue management. The revenue value associated with each point of sale (origin) has been considered when locating seats for a future departure instead of concerning the revenue values of each fare class. Further, it describes a method to obtain optimal seat protection levels that should be reserved from a lower fare origin for a higher fare origin and the nested structure of booking limits for each fare origin so as to optimize the seat allocation in a future departure. A novel approach using Functional Principal Component Regression (FPCR) was carried out to model and forecast the future demand and revenue value for each origin, using historical bookings and revenue values. The Expected Marginal Seat Revenue (EMSR) decision model was developed to address the uncertainty associated with this forecasted future demand and to gain the nested structure of booking limits. Finally, the forecasted booking limits were updated with actual booking *requests prior to the flight departure. At the point of verification, it showed a remarkably maximized total revenue over the existing method. Thus, it is suggested that the optimal seat allocation for a better seat inventory control in airlines can be achieved by jointly utilizing the proposed FPCR and EMSR methods.*

Keywords: Revenue Management, Expected Marginal Seat Revenue, Functional Time Series, Nested Booking Limits, Seat Inventory Control, Optimal Seat Allocation.

1. Introduction

The airlines as global carriers are highly reputed at providing service, comfort and safety for their customers while playing a major role in the global economy. Improving sustainability, they develop and maintain cultural, political and economic affairs around the world. However, the restrictions that arise through competition and various other economic pressures hinder the growth of airlines. Although the airlines utilize optimal fleet assignment techniques to overcome these limitations, the problems still remain when handling uncertainty in demand, perishable inventory and also in price realization (Barnhart et al, 2003). Thus, Airline Revenue Management is employed by airlines as a practice to maximize their revenue. Simply put, it is, "Selling the right seat to the right customer at the right price and the right time" (Annual Report, American Airlines, 1987).

Airlines have some appropriate characteristics for a proper adoption of an effective revenue management method. There is no flexibility to enlarge an aircraft by adding or removing seats. Only possibility is that, for other passengers, it can allocate seats in a later flight. Ability of market segmentation along its customers is another characteristic which creates comparison between price-sensitive and time-sensitive passengers. This will ease the development of marketing strategies for each type of customers. In airlines point of view, the inventory means the seats of the aircraft. The seats which cannot be sold before the departure will result inventory loss. Hence, the seats are called as perishable inventory. If the airlines can minimize this wastage or spoilage of seat inventory, it will operate in more efficient manner. Another tactic that can be used in airline industry is it is possible to sell tickets in advance of actual use. The ticket fares vary all the time, some on hourly basis, others on a weekly basis.

Airlines face with highly erratic demand patterns. The revenue management can be utilized to deal with this uncertainty by smoothing the demand pattern. In peak seasons, they can increase ticket prices to generate more revenue; in valleys, they can decrease the ticket prices by increasing the capacity utilization. The demand for a flight will fluctuate seasonally and also it increases near a few days prior departure. This demand variation can be identified using historical data. For a better revenue management system, not only the fixed capacity but also high capacity change costs are required. That is, the cost of an aircraft is high. On the other hand, selling another seat from available capacity should be relatively inexpensive. The above mentioned characteristics collectively make the path to seek booking policies which can maximize the airlines revenue.

The revenue management (RM) is quantified as being either quantity-based RM or price-based RM if it uses capacity allocation decisions or prices respectively as the primary tactical tool for managing demand. The quantity-based approach involves three principal seat inventory control techniques of RM called, Overbooking, Fare class mix and O-D control (hub and spoke airline network). In fare class mix, booking limits and protection levels for late passengers are identified for each fare class. O-D control gives capability for airlines to manage its inventory by concerning revenue value of the passenger's origin-destination itinerary on the airlines' network. For each technique, Optimization models can be employed to develop revenue maximizing models.

Belobaba (2009) has addressed a comprehensive review on revenue management research based on these techniques employed by the airline industry. Further, Kimes (1989) has mentioned the methods used by previous research and their applicability for a dynamic environment. But, time is of the essence to address the modern requirements, and the modifications to the existing revenue management techniques. That is, it will be necessary to optimize the seat allocation at each point of a sale or the origin. In doing so, the method applied for fare class mix was utilized for the points of sale in this study. Hence firstly, the research has focused on a novel approach to forecasting demand and revenue values for future departures through a better utilization of a Functional Time Series method called Functional Principal Component Regression Analysis. Expected Marginal Seat Revenue method (EMSR) was then used as the revenue management method and the optimal seats protection levels were obtained. Due to the confidentiality of the data, the focus will be only on the methods that were utilized to solve this problem of optimal seat allocation.

2. Methodology

2.1 Functional Principal Component Regression (FPCR) Analysis

Functional data are essentially curves which are considered as single entities rather than merely a sequence of individual observations. The scope of functional data analysis is quite different from time series analysis. While time series analysis focuses on modeling and predicting future observations, the functional data analysis produces shapes and trajectories. This can be applied to unequally-spread datasets and the datasets with missing values as well (Ingrassia & Costanzo, 2005).

The FPCR technique was first suggested by Aguilera, Ocana and Valderrama in 1999. Initially, it captures a time series of continuous functions such as demand within a common bounded interval when the high dimensional data are repeatedly measured on the same object over a period of time. Then for this function, a functional time series model is fitted to obtain forecasts that were h steps ahead (Shang, 2013).

At population level:
The stochastic process f is decomposed into mean function and sum of multiplication of both functional principal components and uncorrelated principal components scores as following.

$$\boldsymbol{f} = \boldsymbol{\mu} + \sum_{\boldsymbol{k}}^{\infty} \boldsymbol{\beta_k} \emptyset_{\boldsymbol{k}} \text{ where} \tag{1}$$

μ - unobservable population mean function
β_k–kth principal component scores
$\emptyset_k$ - kth population functional principal component
At a sample level:
Here the n realizations of f evaluated on a compact interval $x \in [0, \tau]$, denoted as $f_t(x)$ for t = 1, 2,…, n. The functional principal component decomposition is given by

$$\boldsymbol{f_t}(\boldsymbol{x}) = \overline{\boldsymbol{f}}(\boldsymbol{x}) + \sum_{\boldsymbol{k}}^{\boldsymbol{K}} \widehat{\boldsymbol{\beta}}_{\boldsymbol{t,k}} \widehat{\emptyset}_{\boldsymbol{k}}(\boldsymbol{x}) + \hat{\boldsymbol{\varepsilon}}_{\boldsymbol{t}}(\boldsymbol{x}) \text{ where} \tag{2}$$

$\overline{f}(x) = \frac{1}{n}\sum_{t=1}^{n} f_t(x)$- estimated mean function

$\widehat{\emptyset}_k(x)$- k[th] estimated orthonormal eigen function of the empirical covariance operator
$\hat{\beta}_{t,k}$- k[th] principal component score for time t
$\hat{\varepsilon}_t(x)$–the residual
K -the optimal number of components chosen by cross validation

After modeling the functional time series, the h-steps-ahead forecasts denoted by $y_{n+h}(x)$ are obtained by conditioning on the observed data $f(x) = [f_1(x), f_2(x), \ldots, f_n(x)]^T$ and the fixed functional principalcomponents $= \left[\widehat{\emptyset}_1(x), \widehat{\emptyset}_2(x), \ldots, \widehat{\emptyset}_K(x)\right]^T$.

$$\widehat{\boldsymbol{y}}_{\boldsymbol{n}+\boldsymbol{h}|\boldsymbol{n}}(\boldsymbol{x}) = \boldsymbol{E}[\boldsymbol{y}_{\boldsymbol{n}+\boldsymbol{h}}(\boldsymbol{x})|\boldsymbol{f}(\boldsymbol{x}), \boldsymbol{B}] = \overline{\boldsymbol{f}}(\boldsymbol{x}) + \sum_{k}^{K} \widehat{\boldsymbol{\beta}}_{\boldsymbol{n}+\boldsymbol{h}|\boldsymbol{n},\boldsymbol{k}} \widehat{\emptyset}_{\boldsymbol{k}}(\boldsymbol{x}) \quad (3)$$

where $\hat{\beta}_{n+h|n,k}$ denotes the h-step-ahead forecast of $\hat{\beta}_{n+h|k}$ through the univariate time series(Shang, 2013).

This method was used to forecast the demand and revenue value functions for a future departure date based historical booking and revenue data. The functional principal component regression worked well in this scenario since these high-dimensional data (demand/revenue value, days to departure, departure date) were repeatedly observed for the same flight.

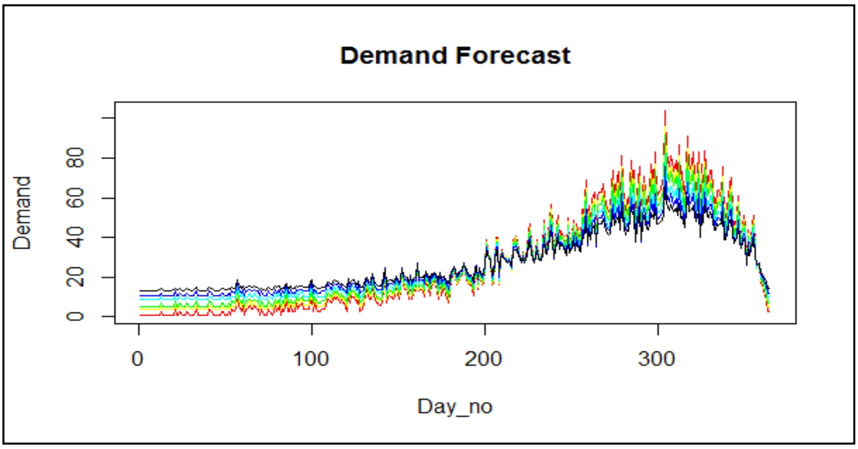

Figure 1: One-step ahead forecast for demand

Figure1 shows an application of this methodology for a fictional set of data. The forecasted demand which is depicted by the black curve and it also shows the same pattern of booking behavior that is visible in original booking data. Beginning with a low demand, it appears to increase within the last consecutive weeks.

Next to generate optimal seat protection levels and nested booking limits, the EMSR method in revenue management was applied for the origins assuming normality in demand for the same origin.

2.2 Expected Marginal Seat Revenue (EMSR) method

The EMSR method for setting nested booking limits was introduced by Belobaba in 1987 (EMSRa) and then developed to become the EMSRb model in 1992. This technique was applied for the fare classes by Belobaba, Odoni and Barnhart in 2009. The EMSR method starts with the higher fare class and using the demand for that class the exact number of seats are protected for the future passenger requests. Then it continues with the next lower class until the authorized capacity of the aircraft is reached. Due to the uncertainty of the future demand, the mean and standard deviation of the forecasted demand are obtained assuming a probability distribution (usually normal). Then the seat protection levels for higher fare classes and booking limits on the lower fare classes are generated (Belobaba, Odoni& Barnhart, 2009).

Several modeling assumptions are made in EMSRb method:

- Demand for each fare class is independent and separate from the demand shows up in other classes.
- Demand for each fare class is stochastic or probabilistic and can be represented by probability distribution (i.e. normal).
- Demand for a given fare class does not depend on the availability of other fare class.
- There are no group bookings, or if they arrive, they can be partially accepted (Talluri, Ryzine, Karaesmen & Vulcano, 2008).

With the intention of modifying the existing method according to the modern requirements the EMSR method was applied for points of sale (origins) where the tickets were issued instead of considering fare classes. This research will focus only on two origins (points of sales) where H will be the origin with the higher ticket price and L is the origin with the lower ticket price. The optimal seat allocation will be generated daily based on the daily passenger demand. Let θ_H be the number of seats that should be held for the origin H passengers and $\boldsymbol{X_H}$ be the demand for that origin on a particular day. Then the expected marginal seat revenue for the origin H should satisfy the condition:

$$\boldsymbol{EMSR_H(\theta_H)} = \boldsymbol{F_H} \times \boldsymbol{P_H(X_H} > \theta_H) = \boldsymbol{F_L} \tag{4}$$

where the F_H denotes the average ticket price for the origin H and F_L denotes the average ticket price for the origin L on a particular day. Once θ_H is computed, the Booking Limit (BL) for the origin L can be derived as:

$$\boldsymbol{BL_L} = \boldsymbol{Capacity} - \boldsymbol{\theta_H}. \tag{5}$$

On day one, the booking limit for origin H (BL_H) is taken to be equal to the full capacity of the plane. Next the procedure could be repeated until the day of the departure by updating BL_H each day to reflect the existing capacity and the forecasted demand for both origins on that day. This procedure can be emphasized as follows. Here the FD is forecasted demand.

Table 1: Nested structure of booking limits

Week no	PL-**H**	FD-**H**	FD-**L**	BL - **H**	BL - **L**
1	θ_1	dh_1	dl_1	$\boldsymbol{capacity} = bh_1$	$\boldsymbol{capacity} - \theta_1$
2	θ_2	dh_2	dl_2	$bh_1 - dh_1 - dl_1 = bh_2$	$bh_2 - \theta_2$
3	θ_3	dh_3	dl_3	$bh_2 - dh_2 - dl_2 = bh_3$	$bh_3 - \theta_3$
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
52	θ_{52}	dh_{52}	dl_{52}	$bh_{51} - dh_{51} - dl_{51} = bh_{52}$	$bh_{52} - \theta_{52}$

Even though this research considered only two origins this methodology could be generalized to find the nested number of seats that should be jointly

protected for any origin i through the $n - i$ origins that have a lower price than origin i.
At the verification step to check whether the final objective had been met, the seat allocations for each origin were obtained using forecasted protection levels and nested booking limits. Then the seats were allocated for each origin according to the following criteria.

“If the booking requests from each origin were within the calculated nested booking limits associated with that origin, they were accepted, and otherwise they were rejected”.

Then, the revenue gain from seats was determined by multiplying with forecasted revenue values for each origin for each day. Also the total revenue was obtained by multiplying the forecasted demand with the actual revenue values for the particular flight. At the validation step, the method showed a considerable revenue enhancement in both above situations when the actual revenue values were used and forecasted revenue values were used. Hence, implementing this novel hybrid model which optimizes the revenue gain significantly, is recommended.

3. Conclusion

At the end of the research: “Airline Ticket Allocation Optimization through Revenue Management”, the following conclusions were brought out.

- Functional time series can be used to model and forecast future demand and revenue values for a given flight-leg using historical booking behavior and revenue values respectively.
- The study recommends the use of the modified EMSR method when generating future seat protection levels for higher priced origins and the nested booking limits to obtain optimal seat allocation with the aim of maximizing the total revenue for an airline.

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