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The impact of customer buying behavior on the optimal allocation decisions

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ABSTRACT

When airlines sell the same or similar seats on an air flight at different fares, the demand for any given fare class depends on the demand for the other fare classes. Demand is affected by customer buying behaviors e.g. diversion, strategic customer behavior. Diversion is denoted for situations when customers buy other fare class tickets if the originally requested fare is unavailable. Strategic customer behavior is used for situations when customers delay a purchase until some point in the future and wait in anticipation of reopening of lower fare. Customer buying behaviors have a considerable profit implication, which was ignored in many earlier studies. We develop an extension of the approach taken by Wilson et al. (2006) to multi-period, multi-fare airline seat inventory allocation decisions and heuristic models with efficient computer algorithms to reduce computation time. Our numerical results are compared with those from the expected marginal seat revenue (EMSR) approach, an exhaustive search, a simulation approach and the approach outlined by Wilson et al. (2006).

1. Introduction

Revenue management (RM) has helped to improve the profitability of service industries such as airlines. McGill and van Ryzin (1999) classified the major areas of airline revenue management as forecasting, overbooking, seat inventory control, and pricing. For airlines, seat inventory control is concerned with decisions on allocating finite flight seat capacity across a set of fare classes. The first published research by Littlewood (1972) provided an analysis of a two-fare model of seat inventory allocation on a single flight leg. He suggested that airlines should close low fare offers when the marginal revenue from selling an additional low fare seat fell below that of selling the same seat at the higher fare. Belobaba (1989) developed a heuristic approach called EMSR (expected marginal seat revenue), in which Littlewood's (1972) rule is applied sequentially in increasing fare order for more than two fare classes. Belobaba also developed a variant of the EMSR method, known as EMSR-b (Belobaba and Weatherford (1996)). The EMSR-b heuristic model provided seat protection levels closer to optimal values than those from the EMSR, which are calculated jointly for all high fare classes relative to a given low fare class based on a weighted combination of all classes above the one for which a booking limit is calculated. Methods for obtaining optimal booking limits with more than two fare classes were provided in Curry (1990), Brumelle and McGill (1993), Wollmer (1992) and Robinson (1995), in which these authors proposed different algorithms to find the optimal allocation. Curry (1990) used continuous demand distributions to find the optimal booking limits for a network of flights, providing an approach to apply his method to origin–destination itineraries instead of to single flight legs. Brumelle and McGill (1993) provided a modified EMSR for nested seat allocation problems. They addressed the problem of determining optimal booking policies for multiple fare classes that shared the same seating pool on one leg of a flight when seats were booked in a nested fashion and when lower fare classes were booked before higher ones. Wollmer (1992) used discrete demands and provided a method for computing both the optimal protection level and the expected revenue. He also used recursive summation instead of integration to derive the optimality condition. Robinson (1995) developed an optimal multi-period approach by using Monte Carlo integration, relaxing the condition that low-fare customers arrived before high-fare ones and assuming that demands across periods were independent of each other. All of the authors consider nested seat allocation RM problems, and the idea of nesting has become quite popular among many researchers. Notable research for nested capacity protection was proposed by Haerian et al. (2006).

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All of these studies above were performed independently, and the demands between fare classes were assumed to be independent under single-period settings. However, demands are actually dependent; many flexible travelers who are willing to pay full price will take a full-fare seat if discount fares are unavailable. This type of customer behavior is called diversion (Pfeifer, 1989). Brumelle et al. (1990) derived optimality conditions with two dependent booking classes by assuming that the demands were independent initially and by considering the effect of diversion. Pfeifer (1989) examined a single-period, two-fare airline seat allocation problem. He assumed that a customer might buy a more expensive ticket if less expensive tickets were not available. Bodily and Weatherford (1995) developed a decision rule for the airline seat inventory allocation problem with customer diversion. They also developed a heuristic algorithm with a generic decision rule for general perishable asset revenue management models. Weatherfordet al (1993) developed Bayesian models for airline revenue management problems with customer diversion by using simulations.

A single-period model yields valuable implications for managers. However, revenue management models that can decide perishable inventory allocations for several periods are desirable and advantageous e.g., Chew et al. (2009), Chew et al. (2014). With respect to multi-period models in the general operations management area, "inter-temporal substitution" describes delaying a purchase until some point in the future. We will use the term "strategic customer behavior" to refer to inter-temporal substitution for airline seat inventory allocations. The EMSR heuristic model can be repeatedly applied to allow for multiple periods. Traditionally the revenue management literature has mostly neglected this issue. However, relevant research on strategic customer behavior issues has been published e.g., Wilson et al. (2006), Aviv and Pazgal (2008), Su (2007), Yin et al. (2008), Lai et al. (2010), Su (2010), Zhao et al. (2012b), Li and Tang (2012), Vaggen et al. (2013).

Many studies of airline seat inventory allocation assume that demand is realized in sales or permanently lost, and that there is no opportunity for customers to wait for future purchasing opportunities. However, customers are becoming more familiar with the pricing and booking structures employed by airline companies, and their buying behavior is becoming more complex. Customers may postpone their purchase decisions in anticipation of an offer of the originally requested fare ticket in the future if they cannot currently buy the tickets at the originally requested fare. Therefore, diversion and strategic customer behavior have more important profit implications for airline seat inventory allocation. Anderson and Wilson (2003) presented a simulation study for multi-period seat inventory allocation problems with diversion and strategic customer behavior, in which protection levels were set by EMSR. Extending the work of Sen and Zhang (1999) and Wilson et al. (2006) developed a two-fare, two-period seat inventory allocation model that considers diversion and strategic customer behavior; strategic customer behavior is specifically denoted for situations in which low-fare customers postpone their purchase decisions because they anticipate a reopening of a lower fare in the next period. Wilson et al. (2006) generated optimal booking limits using an algorithm which has a dynamic-program-like framework. Though Wilson et al.'s (2006) work considers both strategic customer behavior and diversion and provides a theoretical solution procedure for two-fare, two-period problems, finding optimal solutions takes considerable time. The computational complexity of their algorithm when extended to multiple-fare problems increases exponentially. For operations research problem solving, Khouja et al. (1996), Sen and Zhang (1999), Tang and Yin (2007) and Zhao et al. (2012a) considered substitutability, which was equivalent to diversion in the airline revenue management literature. Sen and Zhang (1999) considered a newsboy problem with diversion, which can be applied to airline seat inventory allocations. Diversion was modeled by assuming that a fixed portion of the unsatisfied lower-fare demand would join the higher-fare demand in this research. On the basis of a continuous demand function, Sen and Zhang (1999) provided analytic solutions along with numerical analysis for a single period problem. However, extending their work using continuous demand functions to multiple-fare-class and multi-period problems requires complex calculations. Zhao et al. (2012a) considered a pricing decision problem of substitutable products in a two-echelon supply chain with one manufacturer and two competitors. The authors used game theory approach for two substitutable products.

In this study, we develop heuristic models for solving multi-fare multi-period problems, which is an extension of Wilson et al. (2006), and implement computer algorithms for the heuristic model, in which demands are realized sequentially. We also develop a revised heuristic model with customer choice probabilities, in which customer demands are realized simultaneously. The purpose of this study is to extend the two-fare, two-period airline seat inventory allocations by Wilson et al. (2006) to larger problems and to develop heuristic algorithms that require less time-consuming computation. We find the impact of diversion and strategic customer behavior on optimal solutions and total expected revenues. For numerical examples, we solve three-fare-class, three-period problems using the heuristic approach. The numerical results of the heuristic models are compared with those obtained from EMSR, an exhaustive search, a simulation approach, and the results of Wilson et al. (2006).

2. The model

Throughout the paper, we use the following notations.

C : capacity at the beginning of period 1
c : capacity at the beginning of period 2
c' : capacity at the beginning of period 3
r_j : unit revenue from fare class j ($r_j < r_{j+1}$)
d_{ij} : fraction of diversion (buy − up) customers who cannot buy fare class j will buy fare class $j+1$ in period i
w_i : fraction of waiting customers who cannot buy the lowest fare from period i to period $i+1$
D_{ij} : demand for fare class j in period i
D^*_{ij} : sales for fare class j in period i
$f_{ij}(D_{ij})$: pdf of D_{ij}
$F_{ij}(D_{ij})$: cdf of D_{ij}
l_{ij} : booking limit for fare class j in period i
$E(D_{ij})$: expected demand from fare class j in period i