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# An effective dynamic decision policy for the revenue management of an airline flight

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ABSTRACT

Airline companies normally classify the seats of a cabin class into a number of fare classes. Customers of different fare classes arrive randomly during the booking horizon. Every time a customer in a certain fare class arrives, the airline company must decide promptly whether to fulfill or reject the request. To increase revenues, the airline company may reject certain lower-fare class customer requests and reserve the seats for future higher-fare class customers. However, rejecting too many lower-fare class customers may result in empty seats when the flight takes off. Given the multiple fare classes of a flight and the non-homogeneous Poisson customer arrival process in each fare class, and with the aim of maximizing the revenue of the flight, this study develops and tests two heuristic approaches – the dynamic seat rationing (DSR) decision policy and the expected revenue gap (ERG) decision policy – to help the airline make a fulfillment-or-rejection decision when a customer arrives. The simulation experiments show that ERG performs best among all tested approaches and, on average, the revenue from the ERG being merely 0.8% less than that of the optimal decision made with perfect information. Moreover, the ERG is very robust under various problem conditions.



## 1. Introduction

Optimally allocating finite and perishable inventory to different price classes is a critical issue for a profit-oriented organization. It is obvious that selling inventory items to more profitable orders will increase the revenue, especially when the expected demand is higher than the available inventory. This order fulfillment (or order selection) decision is the focus of revenue management, which has been developed for a number of different industries in the last few decades. For example, recently, Hung and Lee (2010) worked on manufacturing capacity rationing problem, while Hung et al. (2012), Pinto (2012), and Hung and Hsiao (2013) investigated inventory rationing problem. This study focuses on revenue management for the airline industry.

After the deregulation of the airline industry in the 1970s, airline companies were allowed to sell seats in the same cabin for different prices. The reason behind revenue management is that different customers may have different acceptable prices (valuations); thus, airlines will try to sell at a higher price to those customers who are willing to pay a higher price and a lower price to those who will only accept a lower price. Customers arrive randomly during the booking horizon of a flight, which is the duration between the start time for making reservations and the time when the flight takes off. Since the demand for the highest fare class is not enough to fill up a flight, airlines cannot keep all the seats for the highest fare class customers. Also, since the customers of different fare classes arrive at different times during the booking horizon, an airline should not sell too many seats to lower-fare class customers during the early stage of the booking horizon. On the other hand, at the end of the booking horizon, if there are remaining seats, the airline loses revenue due to perished inventory—empty seats. The airline wants not only to sell more tickets to higher-fare class customers but also to sell all of the available seats. Solving such a stochastic trade-off decision problem is the focus of this study.

Airlines classify the seats in a cabin class into different fare classes. The normal practice is that the airline allocates available seats into these fare classes based on the demand forecast for customers with different acceptable prices, and they will reserve the allocated seats for future higher-fare class customers. The number of reserved seats is called the protection level, and the booking limit is calculated by subtracting the protection level from the total available seats. This seat allocation problem has been investigated in full swing, and various approaches have been proposed since the deregulation of the airline industry. In addition, the solution methods can be divided into static and dynamic ones (Lautenbacher and Stidham, 1999; Pak and Piersma, 2002). The static methods assume that the lower-fare class customers always

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come before the higher-fare class customers, so the seat allocation problem is computed at the beginning of the booking horizon (Belobaba, 1987; Brumelle and McGill, 1993; Littlewood, 1972). On the other hand, dynamic methods, without assuming arrival sequence, can adjust the booking limits dynamically based on the latest status when a customer arrives (Lautenbacher and Stidham, 1999; Lee and Hersh, 1993). The methods proposed in this study are dynamic ones.

Pak and Piersma (2002) provided an overview of operations research techniques in solving the seat allocation problem. They classified the methods into single-leg models and network models. In a single-leg model, each flight leg is optimized independently, while in a network model, the objective is to maximize the total revenue of multiple legs. Littlewood (1972) first proposed a static method to solve the single-leg seat allocation problem with two fare classes and used marginal revenues to calculate the number of seats reserved for high-fare class customers. Extending from Littlewood's method, Belobaba (1987) proposed an expected marginal seat revenue method to solve the problem of more than two fare classes. In addition to Belobaba's work, Curry (1990) developed methods to find the optimal booking limits for multiple fare classes. Also, Brumelle and McGill (1993) introduced an approach to solve the optimal protection levels and showed that the obtained revenue is greater than the one by Belobaba. Lee and Hersh (1993) divided the booking horizon into several small decision periods and assumed that at most only one customer arrives in a period. They then approximated the problem using a discrete-time dynamic programming model, which employs a recursive function to calculate marginal revenues and determine whether or not an arrival customer should be accepted. Subramanian et al. (1999) added the assumptions of overbooking, cancellations, and no-shows into the model proposed by Lee and Hersh. Liang (1999) reformulated the assumptions of discrete decision periods of Lee and Hersh's model into a continuous-time frame.

Lautenbacher and Stidham (1999) proposed two Markov decision process models for static and dynamic methods and constructed an omnibus model that assumed there could be more than one customer in a small decision period. Not using demand forecast, Van Ryzin and McGill (2000) introduced an adaptive approach to adjust the protection levels by historical observations. You (2001) developed a dynamic programming model taking into account that rejected lower-fare class customers may be upgraded to the higher-fare class. Haerian et al. (2006) divided the previous booking policies into two booking policies. One is right booking policy, (also called standard nesting policy) and the other is left booking policy (also called theft nesting policy). Glover et al. (1982) were the first to describe the multiple-leg seat allocation problem as a network flow problem and proposed a linear programming model. This model considered a deterministic demand and reserved the exact expected demand seats for the higher-fare class. Williamson (1992) developed an expected marginal revenue model with a probabilistic demand, but there were a large number of decision variables. Extending from Williamson's model, de Boer et al. (2002) proposed a stochastic linear programming model which has fewer decision variables. By using an idea similar to that of dynamic programming, Bertsimas and de Boer (2005) introduced a simulation-based optimization algorithm to improve the booking limits.

The focus of this study is to develop effective dynamic policies that can be applied when a customer arrives to solve the stochastic decision problem with the objective of maximizing the revenue of a flight and without using booking limits.

## 2. Concepts and assumptions

This section describes the problem and the assumptions of the considered revenue management problem for a flight in this study.

1. More than one fare class: Since the prices customers are willing to pay are not the same and the price can be different for the same cabin class, the seats are classified into a discrete number of fare classes.
2. Non-homogeneous Poisson arrival processes: During the booking horizon of a flight, customers in different fare classes arrive randomly. From past experience, the customers searching for a low price (lower-fare class) usually arrive in the early stage of a booking horizon. These customers are price-sensitive and, normally, are tourists who have a well-prepared plan in advance. On the other hand, the customers who can afford to pay a high price (higher-fare class) often come in the later stage; usually, they are business travelers. Most of the previous studies assume that the customer arrival process is homogeneous Poisson; that is, the arrival rate is constant during the booking horizon (Haerian et al., 2006; Lee and Hersh, 1993; Liang, 1999). However, usually, the expected arrival rate fluctuates during a booking horizon. This study assumes that the arrival rate is a function of time and fare class.
3. Independent processes: The customer arrival process of a fare class is independent of the arrival process of another fare class.
4. No overbooking, no cancellations, and no no-shows: Customers whose requests are fulfilled will not cancel their reservations and will show up at the time when the flight takes off. Therefore, the airlines will not book more customers than there are available seats.
5. No demand recapturing: A customer strongly specifies a fare class, and this fare class cannot be upgraded to a higher fare class. If the specified fare class is full, the rejected customer will be lost forever.
6. One seat request: A customer requests only one seat. A customer requesting more than one seat is modeled as several individual arrivals in the non-homogeneous Poisson process.
7. Fixed booking horizon: The duration of the booking horizon for a flight is a known constant.

Each time a customer arrives, by weighting the chance of future higher-fare class customers and chance of empty seat at take-off time, the airline should promptly make a fulfillment-or-rejection decision with the objective of maximizing the total revenue generated by the flight. Under the above assumptions, this study proposes two new dynamic decision policies to handle the decision problem and compares the proposed approaches with several existing ones which are applicable under the assumptions made here.

## 3. Decision policies

This section presents two decision policies: dynamic seat rationing (DSR) and expected revenue gap (ERG). Section 3.1 summarizes the known parameters for the two proposed decision policies. Sections 3.2 and 3.3 thoroughly discuss the two policies, respectively. By using a small example, Section 3.4 demonstrates the two proposed approaches.

### 3.1. Known parameters for decision policies

Let $j$ be the index for fare class (or, briefly, class) and $j=1,2,3,\ldots,J$. The smaller the index value, the higher the fare class. $J$ is the number of fare classes considered. The following parameters are assumed to be known at decision making time:

$s_0$ the initial total available seats at time 0.
$h$ the duration of the booking horizon.
$\lambda_j(\tau)$ the expected arrival rate of class $j$ customers at time $\tau$.