

Summary of Research on Airline Cabin Control

Fangyi Yin ^a

Shanghai University Of Engineering Science, Shanghai 201620, China

^afangyi4017@126.com; ^b844319273@qq.com

Abstract

Airline revenue management is an important technical means for airlines to improve their business. The core content of airline revenue management is cabin control. This paper clarifies the theoretical research and research status of aviation revenue management and space control, including static and dynamic cabin control models for single resource points and static and dynamic cabin control models for multiple resource points. The existing models are reviewed and further proposed. Several questions and directions of research.

Keywords

Cabin control; Static control model; Dynamic control model.

1. Introduction

With the development of the air transport industry, airlines have gradually found that revenue management has made a great contribution to the improvement of operational efficiency, especially for each airline to increase the performance of 2% to 8% per year[1]. As a successful example of the successful use of revenue management information systems, American Airlines has defined revenue management as "the right time and place to sell the right products to the right consumers, with the goal of maximizing revenue. The process of accepting and rejecting reservations selectively."

At home and abroad, there is a study on cabin space. Littlewood[2] first studied the optimization method of single flight section. He assumed that low fare customers would book tickets before high fare customers and studied the cabin control with only two price classes. The problem is raised based on the principle of expected marginal seat revenue for a single flight festival based on two fare classes. Belobaba[3] extended the principle of expected marginal seat revenue for the two-seat single-seat section to multiple cabins and proposed a corresponding heuristic algorithm, which is still widely used. Brumelle[4] and Robinson[5] considered the optimal predetermined control strategy under static seat reservation constraints under the assumption that the reservations for different price classes follow a strict arrival order, and proposed to calculate these reservations. Restricted algorithm. Feng[6] proposed a stochastic control model to dynamically handle cabin control problems. For the network optimization method, De Boer[7] proposed a stochastic linear programming model for the passenger network cabin control problem, and developed the nesting technology before this. Bertsimas[8] applied the simulation method to study the role of nesting techniques in network space control problems. Birbil[9] proposed a framework for solving revenue management problems on large-scale networks.

2. Cabin Control Basic Model

According to the number of resources, the cabin control can be divided into single resource and multi-resource cabin control. Single resource class control refers to the optimal allocation of a resource between different types of requirements. Multi-resource capacity control refers to the sales volume control of multiple related products occupying multiple resources at the same time, also known as network space control. According to the decision rules, the cabin control is divided into static cabin control and dynamic cabin control. The classification diagram of the cabin control model is shown in Figure 1.

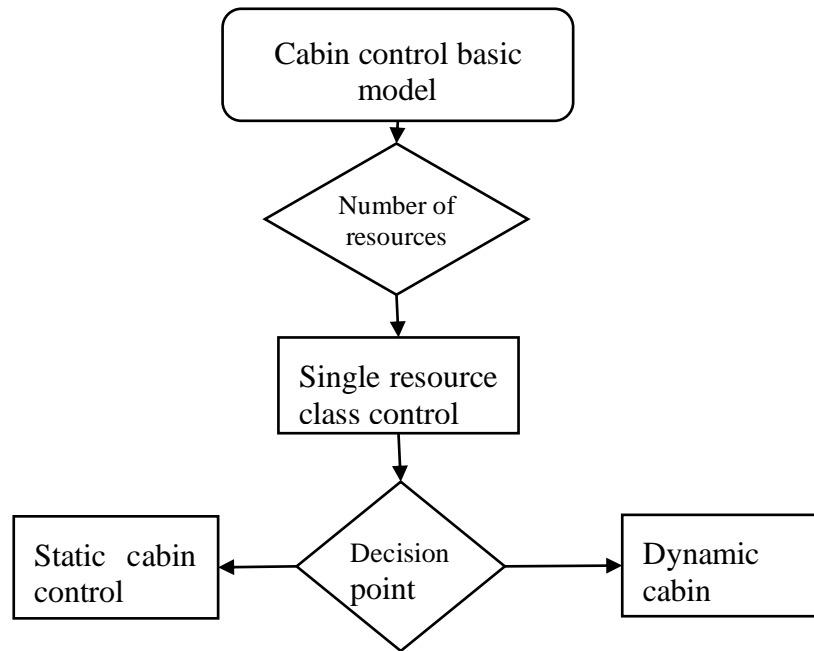


Figure 1 Cabin control control model classification map

3. Single Resource Class Control

3.1 Static control model

The more classic single-resource static cabin control models are the Littlewood model and the EMSR model.

3.1.1 Littlewood cabin control model

The Littlewood cabin control method was first proposed by Littlewood in 1972 for the cabin control problem for a single interval two-tier fare, based on the equal marginal benefit of the two-tier fare. Suppose an airline flight has two fare levels, P_1 is a full price ticket, P_2 is a discount ticket, then $P_1 > P_2$; the number of flight slots is C , no refund or oversell is allowed. $f(P_i)$ is the demand when the fare is P_i , and the distribution function is represented by $F_j(\cdot)$. Assume that the demand of the low price P_2 arrives before the demand of the high price P_1 . If the request is satisfied, the proceeds from the fare P_2 will be obtained; if the request is rejected, the demand $f(P_1)$ of the P_1 should be no less than the remaining seat amount x , satisfy the formula as:

$$P_1 \times P(f(P_i)) < P_2 \tag{1}$$

However, since the demand probability $P(y)$ is a decreasing function with respect to y , the larger the x is, the smaller the P value is. Therefore, the condition satisfied by the above formula has a threshold y^* , that is,

$$P_1 \times P(f(P_i) \geq y^*) > P_2 \tag{2}$$

$$P_1 \times P(f(P_i) \geq y^* + 1) \leq P_2 \tag{3}$$

It can be seen from the above analysis that when P_1 , P_2 and the demand probability $P(y)$ are known, the reserve amount is reserved depending on the remaining number of votes, and y_1^* is called the protection level of the full-price ticket.

$$P_2 = P_1[1 - F_1^{-1}(y_1^*)] \tag{4}$$

$$y_1^* = F_1^{-1}\left(1 - \frac{P_2}{P_1}\right) \tag{5}$$

3.1.2 EMSR Cabin Control Model

The EMSR cabin control method was proposed by Belobaba on the basis of the Littlewood criterion in 1987. He proposed the EMSR9-a and EMSR-b models, both of which are extensions of the Littlewood criterion. By repeating this guideline, the cabin control problem for both fare classes is

extended to the multi-fare rating. The EMSR model assumes that there are n fare classes, the fare $r_1 > r_2 > \dots > r_n$ for different classes, and the customer demand for the lower class arrives before the high class. The arrival phase of type j is also denoted by j , and the fare demand of type n with the benefit r_n arrives at stage n (phase 1), and the type $n - 1$ (stage 2) with the return r_{n-1} arrives. D_j is a random requirement of type j .

1) EMSR-a Model

The basic idea of the EMSR-a model is to accumulate the level of protection for each type at a certain stage to determine the level of protection at this stage. Assuming that the remaining demand in the next stage is only type k , then the problem is transformed into two fare class problems. Using the Littlewood criterion, the protection level y_j^k for type k satisfies the following formula:

$$P(D_k > y_j^k) = \frac{r_{j+1}}{r_k} \tag{9}$$

Let $k = j, j - 1, \dots, 1$, using the above formula (9), the level of protection under each type can be obtained, and the result is summed to approximate the total protection level y_j :

$$y_j = \sum_{k=1}^j y_j^k \tag{10}$$

2) EMSR-b Model

The difference between the EMSR-b model and the EMSR-a model is that the simulation of the EMSR-b model is based on the accumulation of requirements rather than the accumulation of different types of protection levels, which is a good way to avoid statistical average effects. The EMSR-b model accumulates all future needs and treats them as a type of demand, and the accumulated returns equal the weighted average returns of each type. In the $j + 1$ stage, the demand of the $j + 1$ level arrives, and the remaining demand type $j, j - 1, \dots, 1$ protection level y_j needs to be determined, and the remaining total demand is

$$S_j = \sum_{k=1}^j D_k \tag{11}$$

The weighted average return of the remaining types is represented by R_j , then

$$R_j = \frac{\sum_{k=1}^j r_k E(D_k)}{\sum_{k=1}^j E(D_k)} \tag{12}$$

Where $E(D_k)$ represents the expectation of type k requirements. According to the Littlewood guidelines, the protection level y_j is

$$P(S_j > y_j) = \frac{r_{j+1}}{R_j} \tag{13}$$

3.2 Dynamic Control Model

Set the total number of cabins to C , divide the entire pre-sale period into T decision stages, and $t = 1$ and $t = T$ respectively indicate the start and end of the pre-sale period, using $R_t = (R_1(t), R_2(t), \dots, R_j(t))$ represents the stochastic demand of the cabin in the t decision stage. If $R_j(t) = r_j$, it indicates that the customer subscribes to the j type of cabin, the corresponding income is r_j , otherwise $R_j(t) = 0$. Let μ be the decision variable, $\mu = 1$ means accept the reservation request, and $\mu = 0$ means reject the reservation request. Note that $V_t(x)$ indicates the expected return when the number of cabins in the decision stage is x . Then, according to the Bellman optimality principle, there is

$$V_t(x) = E[\max(R_t \mu + V_{t+1}(x - \mu))] \tag{14}$$

Let $\Delta V_{t+1}(x) = V_{t+1}(x) - V_{t+1}(x - 1)$ denote the opportunity cost of the product in the $t + 1$ decision stage, which can be further refined for

$$V_t(x) = V_{t+1}(x) + E[\max \mu (R_t - \Delta V_{t+1}(x))] \tag{15}$$

As can be seen from the above formula, only when

$$r_j \geq \Delta V_{t+1}(x) \quad (16)$$

4. Conclusion

This paper clarifies the theoretical research and research status of aviation revenue management and space control, including static and dynamic cabin control models for single resource points and static and dynamic cabin control models for multiple resource points. It can be seen from the previous analysis that there is still research. problem: (1) The current research on overbooking is mainly from the perspective of the company itself, without considering the influence of competitors. However, this is inconsistent with the actual situation, especially in the domestic airline market, where airlines compete with each other. Therefore, it is very meaningful to consider the overbooking strategy in a competitive environment. (2) There is less research on the flexible cabin control mechanism at home and abroad, and more research is needed.

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