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A simulation analysis for the re-solving issue of the network revenue management problem

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A B S T R A C T

The classic dynamic programming approach is not applicable to the airline network revenue management (RM) problem of a practical size due to the curse of dimensionality. Many heuristic methods, including the most popular bid-price control approach, generate the approximate control decisions based on various static formulations, which need to be re-solved to take into account the dynamic features of the problem. By a simulation experiment, this study examines the re-solving issue of the bid-price method and tests a new method, the parameterized function approach, in which no problem-resolving is required. Based on the results, the parameterized function approach is found to be a promising alternative. As for the bid-price control approach, a high re-solving frequency is needed for a good result.

1. Introduction

Revenue Management (RM), also referred to as Yield Management (YM), has become a common practice in the airline industry ever since American Airlines successfully applied several RM techniques to raise its revenue. Based on certain demand forecasting techniques and optimization models, RM has been found to be very effective in generating extra revenue by dealing with the diversified and uncertain demand, given a fixed capacity. It is very difficult for any major airline nowadays to operate profitably without RM, given that, according to most estimates, the revenue gain from applying RM is about 4%–5%, which is comparable to many airlines' total profitability in a good year (Talluri and van Ryzin, 2004). In addition, RM has been successfully extended to some other industries. For example, a similar result of 1%–8% has been reported for the improvement in profits in the hotel sector (Jones, 2000). Nonetheless, how to realize the basic concept of RM, i.e., selling the right product to the right customer at the right price, remains a challenge.

Due to the current hub-and-spoke operation, the focus of RM research has shifted from the traditional single-leg version to the network version. The problem complexity and the associated computational load make it impossible to derive the optimal control for a problem of practical size. The mainstream approaches, such as bid price and virtual nesting, have some limitations such as the inaccuracy, due to the suboptimal nature, and the interruption in operations, due to the problem-resolving needed for correcting the deficiencies of static models.

The key purpose of this study is to examine the impact of the update frequency for one network RM approach, the most popular bid-price control approach. The control performance in general should be better when the bid prices are updated more frequently. However, it is necessary to achieve a balance between the improved performance and the negative effects (such as the interruption in operations as well as the computational effort required for re-solving the static problem). This study has performed a simulation experiment to examine the re-solving issue of the bid-price approach. In addition to the bases provided by the optimal control and the FCFS (first-come-first-served) policy, the results are compared with a new method, the approach based on the parameterized function for revenue approximation (Huang and Liang, 2011), in which no problem-resolving is needed.

The remainder of this paper is organized as follows. The second section provides the problem background and reviews the related literature. The bid-price method, the method based on the parameterized function for revenue approximation and the framework of the simulation experiment are presented in the third section. The numerical experiment is described in the fourth section. Finally, the findings of this study are summarized and conclusions are drawn in the final section.

2. Background and literature review

Researchers have studied various kinds of seat inventory control problems for airlines. Weatherford and Bodily (1992) provide a very

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general approach to categorize the nature of RM problems, and McGill and van Ryzin (1999), Talluri and van Ryzin (2004) and Chiang et al. (2007) serve as an excellent reference of the research literature on RM. The literature review of this study focuses on the RM problem within the network context.

In an airline network, a fare class of an origin-destination pair (later referred to as an ODF) can utilize the seats of multiple legs, and a seat on a leg is usually shared by multiple ODFs. The network RM problem incorporating this network feature and the dynamic characteristics of the demand can be formulated as the following DP model (Talluri and van Ryzin, 2004).

$$V_t(\mathbf{x}) = P_t^0 V_{t-1}(\mathbf{x}) + \sum_{j=1}^{J} P_t^j \max\left(V_{t-1}\left(\mathbf{x}-\mathbf{S}^j\right) + F_j, V_{t-1}(\mathbf{x})\right) \tag{1}$$

where $P_t^0 = 1 - \sum_{j=1}^{J} P_t^j$

- t: indices of decision periods ($t = 0$ .. T, assuming $t = 0$ is the period of flight departure, and $t = T$ is the beginning of the booking process.)
- j: indices of ODFs ($j = 1$ .. J)
- P_t^j: probability of the booking request for ODF j in period t
- F_j: revenue of ODF j
- i: indices of legs ($i = 1$ .. I)
- $\mathbf{S}$: an incident matrix ($I \times J$), representing the relationship between the ODFs and the legs. Its entry s_{ij} is equal to 1 if ODF j uses leg i; otherwise, it is 0.
- $\mathbf{S}^j$: the jth column vector of $\mathbf{S}$, representing the legs used by ODF j.
- x_i: the number of available seats on leg i, and the vector $\mathbf{x}$ represents the available seats on all legs.
- $V_t(\mathbf{x})$: expected revenue given the available seats on the legs $\mathbf{x}$ in period t

The Bellman equation of the DP model (1) shows how to evaluate the expected revenue given the arrival information of the demands in a recursive manner. With the boundary condition $V_0(\mathbf{x}) = 0$ at the end of the booking process (flight departure), the objective is to maximize the expected revenue $V_T(\mathbf{C})$ given $\mathbf{C}$ seats available on the legs (*i.e.*, the system capacity) at the beginning of the booking process.

The optimal control policy that results in the maximum expected revenue can be generated by (2) based on the two terms inside the max function of (1). For each period t given the available seats on the legs $\mathbf{x}$, a booking request of ODF j should be accepted if its revenue is larger than the expected revenue decrease due to state change (*i.e.*, the opportunity cost) in period (t-1). The computational load to evaluate the expected revenue for (1) and then to generate the optimal control policy based on (2) for the entire state space is intractable for most practical problems. Thus, an approximate algorithm with a manageable computational load and acceptable solution quality is usually used.

$$F_j \geq V_{t-1}(\mathbf{x}) - V_{t-1}\left(\mathbf{x}-\mathbf{S}^j\right) \tag{2}$$

The most popular approach for the network RM problem is the bid-price control approach, as it is intuitive and easy to implement (Escudero et al., 2013). A bid price is attached to each leg, and a booking request for a fare class of an origin–destination pair is accepted if its revenue is greater than the sum of the bid prices of the used legs. The key issue of most bid-price based algorithms is to find a suitable set of bid prices, which is supposed to depend on the number of seats available on the legs and the number of time periods left before departure. Williamson (1992) set the bid prices as the dual prices of the leg capacity constraints in a static linear programming (LP) model, in which the demand patterns of the ODFs are replaced by the point estimations regarding the remaining periods as a whole. Thus, frequent updates of bid prices during the booking process are generally required. The other issue associated with Williamson (1992) was that the stochastic feature of the demand was overlooked in the deterministic LP model. Many researchers have focused their efforts on the sophisticated algorithms used to generate better bid prices to address the dynamic and/or stochastic feature of the problem. For some recent works, please refer to Adelman (2007), Topaloglu (2008), Akan and Ata (2009), Ball and Queyranne (2009), Topaloglu (2009), Kunnumkal and Topaloglu (2010), and Escudero et al. (2013). In particular, more and more network RM models (*e.g.*, Meissner and Strauss, 2012) have taken into account the choice behavior of customers, which is a feature not considered in this study.

Nonetheless, the classic bid-price method based on a static and deterministic LP model, such as Williamson (1992), is still widely used in practice (Chen and Homem-de-Mello, 2010), and re-solving the problem to update the bid prices remains an important issue for implementing the network RM control. In general, the performance should be improved if the bid prices are updated more frequently, as the actual situation of the demand and seat availability can be taken into account in a timely manner. However, this intuitive speculation needs to be examined and it would be better if it were supported by some numerical analysis. Even more importantly, it is necessary to find a balance between the improved control accuracy and the negative effects.

Cooper (2002), the first to address the re-solving issue of the bid-price control method, showed that re-solving does not necessarily lead to a better result based on a very simple single-leg example. From the aspect of the general control-algorithm approach, Secomandi (2008) established sufficient conditions under which re-solving does not worsen the performance of the control policy. In addition, the counter-intuitive example in Cooper (2002) was re-visited in a numerical experiment, in which eight control policies were compared. Chen and Homem-de-Mello (2010) dealt with the original multi-stage stochastic network RM problem by means of an approach where they solved a sequence of two-stage stochastic programming (SP) problems with simple recourse. Their theoretical results show that solving more successive two-stage SP problems can never result in a reduction in expected revenue. In addition, they also proposed a heuristic method to determine the re-solving schedule, in which the updates are not evenly spaced within the booking horizon. Recently, Jasin and Kumar (2012) derived an upper bound for the expected revenue loss of various re-solving control policies, when compared with the optimal control, and further designed two re-solving schedules with bounded asymptotic revenue loss.

Huang and Liang (2011) have developed a new control method for the network RM problem, in which the dynamic decision is based on the parameterized functions, which approximate the expected revenues for the entire state space in terms of seat availability. As the parameters of the functions for all time periods can be estimated in advance, no update is required for this approach. Given this special advantage, this method is also tested in the simulation experiment to serve as a basis for performance evaluation, in addition to the optimal control and the FCFS (first-come-first-served) policy. Meanwhile, beyond the purpose of examining the bid-price control method in terms of the re-solving frequency, this study also aims to evaluate the applicability of the method based on parameterized functions in Huang and Liang (2011) to the network RM problem.