Behavioral Tendencies in Revenue Management Decision Making

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1 Introduction

The problem of how to optimally allocate the capacity of a perishable resource among different classes of demand with the aim of maximizing total revenues is a well-studied problem in the literature. In this study, we refer this problem as a Perishable Asset Revenue Management (PARM) problem. PARM problems are also called yield management problems and have been studied under variety of contexts ranging from managing broadcast advertising, freight transportation, to cruise ship sales (Talluri and Van Ryzin, 2004). For a taxonomy of PARM problems, we refer the reader to Weatherford and Bodily (1992).

There exits substantial literature which focuses on the theory of Revenue Management (RM). Some of the most important results are provided by Gerchak et al. (1985), Belobaba (1987), Brumelle and McGill (1993), and by Lee and Hersh (1993). A comprehensive survey of this topic is provided by McGill and Van Ryzin (1999). However, to the best of our knowledge Bearden et al. (2008) provide one of the only reported study which questions whether the human decision makers have biases in RM decision making. With this study, we aim to fortify the experimental studies of RM.

There are some industries such as airlines and hotels in which RM practices are well developed and sophisticated software implementations for decision making are being utilized. However, the usefulness of the analytical models of RM is not restricted to these industries. There also exist variety of settings in which RM decisions are made by human decision makers. The examples include taking reservations at a restaurants, ticket sales for theater and sporting events, deciding how much beer to deliver at each store along a delivery route (Bassok and Ernst, 1995), or even how many bagels to reserve for sandwiches at lunch (Gerchak et al., 1985). For instance, in the latest, there exists a salesman who faces the decision of how to allocate product(s) to each of the customers. Similarly, the decision of accepting or rejecting a reservation request at a restaurant is made by the manager or an employee of the restaurant.

Our goal in this study is to confront human decision makers, in a controlled laboratory environment, with RM decision problems for which the optimal policies are known. Based on the results we obtain, we expect to observe whether human decision makers have any behavioral regularities in making RM type of decisions. If there exist any anomalies, how they affect and what implications do they have for

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revenue management. We expect our results to provide insight, and therefore be useful for managers who are faced to make RM decisions in practice.

2 Perishable Asset Revenue Management (PARM) Problem

We consider a firm which sells its capacity (C) at two prespecified prices (i.e, at low-revenue and highrevenue). The capacity is fixed, more precisely the cost of increasing capacity in short run is considered as very high. The capacity is also perishable which means that there is a deadline after which you cannot sell the units of this capacity. Let R_H (resp., R_L) be the revenue per unit from a high-revenue (resp., low-revenue) customer. The units of capacity are assumed homogenous, and customers demand a single unit of capacity for the resource. We assume that demands for different classes are independent random variables. A denied customer does not attempt to upgrade to the high-fare class or downgrade to the low-fare class and is simply lost. There are no cancellations. We assume that prices are fixed, and we attempt to maximize revenue without changing prices. Then, the central problem is how to optimally allocate the capacity of the resource among two classes under considerable uncertainty of future demand in order to maximize revenue.

The assumptions of this simple model are restrictive when compared to real-life problem, however the results of this simplified problem can provide insights for more realistic models. There also exist some methods in which this simple model is being used as a building block to obtain a solution to more complex cases. For the sake of simplicity, we focus on single resource model with two classes.

Next, we explain the theoretical models that we consider.

3 Theoretical Models

We consider the PARM problem under three different settings. The differences of each setting and the optimal policy for the problem under each setting is provided below.

Model 1: Static Model

We start with the simplest setting. In this model, we assume that demand for different classes arrives in nonoverlapping intervals in the order of increasing prices of the classes, i.e., low-fare demand arrives before high-fare demand.

This model requires only an estimate of the probability distribution of the total demand for each fare class, and does not need to explicitly consider the passenger arrival process over time. Then, the problem is to decide *how much capacity to reserve for high-fare customers*, or equivalently how much low-fare demand to accept before seeing the realization of high-fare demand.

• <u>Optimal policy</u>: The optimal solution which maximizes the expected revenue can be stated in terms of *protection level*, i.e., the number of units that must be protected for high-fare customers.

The optimal protection level y^* is given as follows:

$$y^* = F_H^{-1} (1 - \frac{R_L}{R_H}) \tag{1}$$

where F_H^{-1} is the inverse demand function for the high-fare class. In literature, this rule is known as Littlewood's rule (Littlewood, 1972).

We want to note that this model –with the assumption that low-fare demand arrives before high fare demand– has a close relationship to newsvendor problem in inventory theory. The optimal solution can also be obtained by finding the critical fractile as in newsvendor problem.

Model 2: Dynamic Model - Ordered Arrivals

In this model, we have the same underlying setting as in Model 1. That is, we assume that low-fare demand arrives before high-fare demand. Instead of considering an aggregate quantity of demand arrives in a single stage (as in Model 1), here we consider demand arrives in discrete time periods according to some probabilities. The reservation horizon is finely discretized in such a way that the arrival processes of customers results in the same demand distributions in Model 1. Accordingly, the format of decision making also changes in this model. As a counterpart of deciding a protection level in Model 1, this model requires making a set of sequential decisions of whether to accept a particular demand at its arrival time. The problem in this model is to decide *how much low-fare demand to accept before seeing the realization of high-fare demand*.

• <u>Optimal policy</u>: Since there exist only two classes, and we assume that low-fare demand arrives before high-fare demand, the optimal policy of Model 1 remains optimal for this model.¹ Thus, $C - y^*$ of low-fare demand must be accepted before seeing the realization of high-fare demand, where y^* is given by Equation 1.

Model 3: Dynamic Model - Unordered Arrivals

Same as in Model 2, we consider demand arrives in discrete time periods according to some probabilities. Different from Model 2, we allow customers to arrive in arbitrary order throughout the reservation horizon (i.e., we remove the low-fare demand arrives before high-fare demand assumption) in this model. The question here is *whether to accept or reject a particular demand at its particular arrival time*.

• <u>Optimal policy</u>: Note that this is the most complicated model among three models and obtaining optimal policy requires solving a dynamic program (DP). The optimal policy can be found by applying the method provided by Lee and Hersh (1993) and is summarized below.

¹For more general case with *n*-classes, Brumelle and McGill (1993) show that the problem is monotone optimal stopping problem. As a result, static control limit policies are optimal over the class of all control policies for this problem, including dynamic ones.

- * A request for high-fare class will always be accepted as long as the capacity is not exceeded.
- * Whenever a low-fare customer arrives, accept it if $R_L \ge \Delta(x, t-1)$, and reject it otherwise; where threshold $\Delta(x, t-1)$ indicates the expected marginal value of a unit at time t with x remaining units.

4 Experimental Design

We plan to use a set of controlled laboratory experiments to test our hypothesis. We design three experiments each corresponding to one of the models explained in Section 3. All three experiments have the same general setup, use incentive-compatible payoffs to encourage subjects for careful decision making, and promote learning.

We use a 3×2 between-subjects full factorial design with three levels of decision dynamics and two different high type arrival distributions. Thus, in total, we have 6 treatments.

The experiments differ in decision making format. Specifically, subjects are either asked to make onetime decision at the beginning of reservation horizon (Experiment 1), or asked to make an accept/reject decision for each arrival throughout the reservation horizon (Experiments 2 and 3).

In all experiments, we fix C = 10, $R_H = 200$ and $R_L = 120$.

In Experiment 1, the total demand distribution of low-fare customers is Poisson with parameter $\lambda_L = 15$ and the total demand distribution of high-fare customers is Poisson with parameter $\lambda_H = 5$. In Experiment 2, the total demand distributions of both low-fare and high-fare customers remain the same. We finely discretized the reservation horizon into time intervals and for each time interval we obtain the arrival probabilities for each customer class (using the method provided by Lee and Hersh (1993)). Thus, in each time interval a low-revenue customer arrives with probability $p_L = 0.0476$, and a high-revenue customer arrives with probability $p_L = 0.0476$, and a high-revenue customer arrives with probability $p_H = 0.0083$. We want to keep the expected number of low-fare customers, the expected number of high-fare customers (thus, the expected number of total arrivals) as the same across all three experiments. This resulted in different arrival probabilities in Experiments 2 and 3.

For each treatment, we plan to have thirty-five subjects and run the treatment for 40 rounds. We summarize the design parameters for each experiment in Table 1 below.

	C	R_H	R_L	D_H Distibution	D_L Distibution	Arrival Probabilities
Experiment 1	10	200	120	$Poisson(\lambda_H = 5)$	$Poisson(\lambda_L = 15)$	
Experiment 2	10	200	120		_	$p_H = 0.0164 \ p_L = 0.0476$
Experiment 3	10	200	120			$p_H = 0.0083 \ p_L = 0.0244$

Table 1: Experimental Parameters Across Experiments

 D_H : High-fare demand and D_L : Low-fare demand.

We now proceed to formulate our hypotheses.

5 Hypotheses

We formulate our hypotheses to measure the extent to which behavior of RM decision makers complies with the theoretical predictions.

HYPOTHESIS 1. In Model 1, the expected protection level set by decision makers is y^* .

HYPOTHESIS 2. In Model 2, the expected low-fare demand to be accepted before seeing the realization of high-fare demand is $C - y^*$.

HYPOTHESIS 3. The solution to PARM problem under the assumption of low-fare demand arrives before high-fare demand is invariant to the framing of the problem. That is, the solutions to Model 1 and Model 2 are equal.

HYPOTHESIS 4. In Model 3, the acceptance decisions made for low-fare customers follow the threshold rule of $R_L \ge \Delta(x, t-1)$, where R_L is the low-fare revenue and $\Delta(x, t-1)$ is the threshold value indicating the expected marginal value of a unit at time t with x remaining units.

6 Future Work

We continue with running the experiments in laboratory. We plan to complete data collection and analyze our results in the next few months.

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